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Assessment of Quality of Experience of High Dynamic Range Images Using the EEG and Applications in Healthcare

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Assessment of Quality of Experience of High Dynamic Range Images Using the EEG and Applications in Healthcare

By
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Author's Declaration

At no time during the registration for the degree of Doctor of Philosophy has the author been registered for any other University award without prior agreement of the Doctoral College Quality Sub-Committee. Work submitted for this research degree at the University of Plymouth has not formed part of any other degree either at the University of Plymouth or at another establishment.

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Date ....

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Assessment of Quality of Experience of High Dynamic Range Images Using the EEG and Applications in Healthcare

Shaymaa S Al-juboori

Abstract

Recent years have witnessed the widespread application of High Dynamic Range (HDR) imaging, which like the Human Visual System (HVS), has the ability to capture a wide range of luminance values. Areas of application include home-entertainment, security, scientific imaging, video processing, computer graphics, multimedia communications, and healthcare.

However, in practice, HDR content cannot be displayed in full on standard or low dynamic range (LDR) displays, and this diminishes the benefits of HDR technology for many users. To address this problem, Tone-Mapping Operators (TMO) are used to convert HDR images so that they can be displayed on low-dynamic-range displays and preserve as far as possible the perception of HDR. However, this may affect the visual Quality of Experience (QoE) of the end-user.

QoE is a vital issue in image and video applications. It is important to understand how humans perceive quality in response to visual stimuli as this can potentially be exploited to develop and optimise image and video processing algorithms. Image consumption using mobile devices has become increasingly popular, given the availability of smartphones capable of producing and consuming HDR images along with advances in high-speed wireless communication networks.

One of the most critical issues associated with mobile HDR image delivery services concerns how to maximise the QoE of the delivered content for users. An open

research question therefore addresses how HDR images with different types of content perform on mobile phones.

Traditionally, evaluation of the perceived quality of multimedia content is conducted using subjective opinion tests (i.e., explicitly), such as Mean Opinion Scores (MOS). However, it is difficult for the user to link the quality they are experiencing to the quality scale. Moreover, MOS does not give an insight into how the user feels at a physiological level in response to satisfaction or dissatisfaction with the perceived quality. To address this issue, measures that can be taken directly (implicitly) from the participant have now begun to attract interest. The electroencephalogram (EEG) is a promising approach that can be used to assess quality related processes implicitly. However, implicit QoE approaches are still at an early stage and further research is necessary to fully understand the nature of the recorded neural signals and their associations with user-perceived quality. Nevertheless, the EEG is expected to provide additional and complementary information that will aid understanding of the human perception of content. Furthermore, it has the potential to facilitate real-time monitoring of QoE without the need for explicit rating activities.

The main aim of this project was therefore to assess the QoE of HDR images employing a physiological method and to investigate its potential application in the field of healthcare.

This resulted in the following five main contributions to the research literature:

1. A detailed understanding of the relationship between the subjective and objective evaluation of the most popular TMOs used for colour and greyscale HDR images. Different mobile displays and resolutions were therefore presented under normal viewing conditions for the end-user with an LDR display as a reference. Preliminary results show that, compared to computer

displays, small screen devices (SSDs) such as those used in smartphones impact the performance of TMOs in that a higher resolution gave more favourable MOS results.

2. The development of a novel Electrophysiology-based QoE assessment of HDR image quality that can be used to predict perceived image quality. This was achieved by investigating the relationships between changes in EEG features and subjective quality test scores (i.e. MOS) for HDR images viewed with SSD.
3. The development of a novel QoE prediction model, based on the above findings. The model can predict user acceptability and satisfaction for various mobile HDR image scenarios based on delta-beta coupling. Subjective quality tests were conducted to develop and evaluate the model, where the HDR image quality was predicted in terms of MOS.
4. The development of a new method of detecting a colour vision deficiency (CVD) using EEG and HDR images. The results suggest that this method may provide an accurate way to detect CVD with high sensitivity and specificity (close to 100%). Potentially, the method may facilitate the development of a low-cost tool suitable for CVD diagnosis in younger people.
5. The development of an approach that enhances the quality of dental x-ray images. This uses the concepts of QoE in HDR images without re-exposing patients to ionising radiation, thus improving patient care. Potentially, the method provides the basis for an intelligent model that accurately predicts the quality of dental images. Such a model can be embedded into a tool to automatically enhance poor quality dental images.

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List of abbreviations and glossary

ACC	Accuracy
ADHD	Attention-Deficit/Hyperactivity Disorder
ANOVA	Analysis of Variance
CI	Confidant interval
CRF	Camera Response Function
CSF	Contrast sensitivity function
CVD	Colour Vision Deficiencies
DS	Double stimuli
EEG	Electroencephalography
ERP	Event-Related Potential
FNR	False Negative Rate
FPR	False Positive Rate
HDR	High Dynamic Range
HDR-VDP	High Dynamic Range-Visible Differences Predictor
HVS	Human Visual System
iCAM	Image Colour appearance model
ITU	International Telecommunication Union
JND	Just Noticeable Difference
JPEG	Joint Photographic Experts Group
KRC	Kendall rank correlation

LDR	Low Dynamic Range
MCC	Matthew’s correlation coefficient
MOS	Mean Opinion Score
mPSNR	Multi-Exposure Peak Signal-to-Noise Ratio
MSE	Mean Squared Error
NPV	Negative predictive value
PD	Parkinson Disease
PLC	Pearson linear Correlation
PPV	Positive predictive value
QA	Quality Assurance
QoE	Quality of Experience
QoS	Quality of Service
RGB	Red-Green-Blue
RMSE	Root Mean Squared Error
SE	Shannon Entropy
SNR	Signal-to-Noise Ratio
SRC	Spearman Rank Correlation
SS	Single stimuli
SVM	Support Vector Machine
TIFF	Tagged Image File Format
TMO	Tone Mapping Operator
VDP	Visible Differences Predictor

Chapter 1 Introduction

High Dynamic Range (HDR) imaging provides the ability to capture a wide range of luminance values, similar to that of the human visual system, and this has led to its widespread application in many areas including home entertainment, medicine, scientific imaging, computer graphics and multimedia communications which motivated the setting up of this project.

Traditionally, perceived Quality of Experience (QoE) of multimedia content can been assessed using subjective opinion tests, such as the Mean Opinion Score (MOS)[1]. However, MOS does not give an insight into how the user really feels, at the physiological level, in response to dislikes or satisfaction with the perceived quality [3]. The use of the EEG aims to address this issue [2]. When HDR images are viewed and subjects are assessing image quality, this provoke changes in their EEG wave activities. The main thread of the thesis are twofold. Firstly, to find the best TMO can be used to assess QoE. Second, to apply HDR images on medical applications.

This Chapter presents the motivations behind the project and the fundamental research questions to be addressed. Further, it outlines the aims and objectives of the project and presents the main contributions to knowledge. The Chapter is arranged as follows. Section 1.1 presents the motivations behind the project. The research questions are given in Section 1.2. Section 1.3 presents the project aims and objectives. The main contributions are summarized in Section 1.4 and a brief overview and organisation of the thesis are given in Section 1.5.

1.1. Motivations

When natural scenes are captured in the conventional imaging format, some of details that the human visual system (HVS) can capture are lost because of the limited dynamic range of the conventional low dynamic range (LDR) imaging. The high dynamic range (HDR) imaging is expected to reproduce natural lighting better than the

LDR imaging and preserve fine details better using a higher dynamic range. For this reason, Tone-Mapping Operators (TMO) are used to convert HDR images so that they can be displayed on LDR displays and preserve as far as possible the perception of HDR.[3] [4]. Numerous studies have been undertaken to evaluate the performance of TMO, most using large conventional displays such as those of TV sets and PC monitors and only a very few using small screen devices (SSDs) such as those of mobile phones [3] [4] [5] [6].

Recently, image consumption using SSDs has become increasingly popular because of the availability of smartphones and tablets capable of producing and consuming HDR images and advances in high-speed wireless communication networks. One of the most critical issues in mobile HDR image delivery services is how to maximize the Quality of Experience (QoE) of the users for the delivered contents[5], [6]. An open research question is how HDR images with different contents perform on mobile phones.

Ultimately, the goal of the HDR imaging is to deliver better QoE of visual contents to end-users. Methodologies of multimedia QoE measurement can be divided into two general categories: explicit approaches and implicit approaches. The former indicates the traditional subjective assessment, where users rate target contents explicitly, such as Mean Opinion Scores (MOS) [7]-[10]. However, it is difficult for the user to link the experienced quality to the quality scale. It has been adopted popularly for understanding QoE; however, in recent years implicit approaches are actively studied. Instead of asking users to rate perceived QoE, the implicit approaches monitor physiological signals changing due to the perceptual mechanism[10].

Among various physiological signals, cerebral physiological signals, such as electroencephalography (EEG), functional magnetic resonance imaging (fMRI), and functional near-infrared spectroscopy (fNIRS), have been mainly studied because they contain high-level cognition information with high temporal and spatial resolutions in comparison to peripheral physiological channels such as galvanic skin response, body temperature, heart rate, etc. [1], [11].

Recently, EEG has been used to assess the QoE of multimedia content [1], [12]-[16].. A number of studies have demonstrated that changes in the quality of images and videos can be detected in the EEG using power spectral analysis. The EEG is non-invasive, low-cost, has a high temporal resolution and provides valuable information about brain dynamics [17][18][19][20][21][22][23].

HDR is increasingly used in many applications to create visually pleasing images especially scenes that contain bright, direct sunlight to extreme shade, or very faint shades [24][25]. HDR images represent a wide range of luminance levels, which reproduce realistic and visually appealing content for different shades of colour and amount of light in images that is close to reality. For these reasons, we have been motivated to use HDR images in healthcare applications such as the assessment of Colour Vision Deficiency (CVD) and dental X-Ray enhancement.

CVD is an inability to distinguish certain shades of colour that affects the everyday lives of many young people. CVD can cause numerous real-life problems, ranging from minor frustrations to difficulties that affect safety and threaten the professional lives of those affected[26], [27]. It is therefore recommended that children experiencing trouble in school should be tested for vision problems, including CVD. However, the widely used diagnostic for CVD, the Ishihara plate test, is time-consuming and is unsuitable for screening children who are unable to articulate the numbers they can see [28], [29]. Consequently, about 80% of pupils are not tested for CVD and approximately 40% of colour-blind pupils leave school unaware that they have this condition [30]. When HDR images are viewed and subjects are assessing image quality, this causes changes in the EEG, which may be associated with detecting CVD.

The use of X-rays is an integral part of clinical dentistry as radiographic examinations are an irreplaceable and special investigative tool necessary for most patients [31]. X-ray exposure carries a risk for the patient; therefore, it is essential that any x-ray examination should provide a potential net benefit. This implies weighing the diagnostic benefits it provides against the potential detriment such exposure might cause [32]. HDR imaging is an important new development that can be used to enhance image quality and reduce the number of unacceptable radiographic images. Improving the quality of dental x-ray images, without re-exposing patients to ionising radiation, will enhance the diagnostic power of radiographs and improve patient care [33], [34].

Our main observations are therefore that:

- Detailed investigation into QoE for the end user (end user is a person who ultimately uses or is intended to ultimately use a product) on SSDs has yet to be conducted. Screen resolution and size are now regarded as two key factors in the choice of SSDs. However, whether an increase in screen size and resolution improve the QoE when viewing HDR images remains unclear. Moreover, even if they do improve the QoE, how substantive is this gain. To optimise the visual experience for the user, it is important to consider whether certain TMOs are preferred when watching HDR images on SSD devices [35].

- Concern has grown in the visualisation and scientific communities regarding the QoE of grey HDR imagery in scientific applications [36]. There are two aspects to this concern: (1) The implementation of HDR algorithms including those used for HDR grey images, and (2) the psychophysical evaluation of these algorithms in tone-mapping grey images. The results from the evaluation can therefore be used as feedback to help improve the algorithms used to encode the data [37].

- Limited research has been conducted on QoE models to predict users' acceptance of mobile HDR images[38]. This is partly because modelling QoE is challenging due to the difficulties involved in representing a complex, subjective measure of user experience in a simple and objective way [model paper]. QoE measurement is also difficult due to the variability and complexity of human behaviour, where preferences, feelings or perceptions about a service or product may diverge considerably. Although challenging, use of the brain wave (i.e., the EEG) [12-14], potentially provides a powerful way to understand human behavioural states and transform them into meaningful data while viewing HDR images.
- Physiological signals, such as the EEG, have shown promise in revealing the levels of emotion or attention expressed in the assessment of image quality and the correlation of these with media service quality[39]-[41] [42]. However, it is difficult for the user to link the quality they experience to the quality scale[41]. Moreover, at a physiological level, MOS does not give an insight into how the user really feels in response to satisfaction or dissatisfaction with the perceived quality[43].
- On the other hand, modelling QoE is challenging due to the variability and complexity of human behaviour, as people's preferences, feelings or perceptions about a service or product will differ [10]. Moreover, research aimed at establishing models to predict users acceptance of mobile images is limited [7] [10] [12]. Furthermore, user perceptions and preferences continually change over time. The challenge is therefore how to better understand human behavioural states and transform them into meaningful data [44].

- CVD affects the everyday lives of a large number of people; the standard CVD test is the Ishihara plate test, which measures the numbers participants can see in a coloured set of dots situated within another circle of different coloured dots [45][46]. The accuracy of this test may decrease with time, it is expensive, and it cannot be used to screen for CVD in younger children[30]. To address these problems, we proposed a new diagnostic approach based on the relationships between the EEG characteristics of a person with CVD. EEG is non-invasive, low-cost, has a high temporal resolution, and provides valuable information about brain dynamics[41][47].

- To enhance radiographic images using HDR techniques, at least two poor quality radiographs from the same participants should be used due to the requirements of processing [4], [24]. However, as noted previously, X-ray exposure presents a risk to the patient [33][34], [48]. We therefore propose that only one poor quality radiograph should be used to minimise exposure to radiation.

1.2. Research questions

This dissertation addresses the following questions/issues:

Q1) In terms of visual quality, what is the best TMO to use for SSD and LDR displays? What impact do the different sizes and resolutions of SSDs have on the Quality of Experience of HDR images?

Research was conducted to investigate the relationships between tone-mapping operators and viewing devices and their effect on the visual quality of experience. Using both subjective and objective methods, we evaluated the most popular tone-mapping operators in different mobile displays and resolutions under normal viewing conditions of the end-user. Preliminary results show that, compared to computer displays, small screen displays (SSDs) have an impact on the performance of TMOs.

In general, the larger the mobile resolution, the better the subjective results. We also found clear differences between the performance of SSDs and LDRs. The best TMO for mobile displays is iCAM06 while for computer displays it is Photographic Reproduction.

This work will be discussed in Chapter 3.

Q2) Can Tone Mapping Operators (TMO) processing techniques designed mainly for colour HDR images improve visual QoE for greyscale HDR images in different viewing devices (LDR and SSDs).

In this thesis, a subjective and an objective evaluation for commonly used TMOs has been performed in different displays and resolutions for colour and greyscale HDR images. Our results show that viewing devices have an influence on the performance of TMOs, suggesting the need for a careful choice of TMO to enhance the visual quality of experience of the end-user. As expected, the higher the resolution, the better the HDR-image quality. Surprisingly, there was no significant difference between the scores for colour and grey images in SSDs. The device and TMOs thus have an equal effect on QoE for colour and grey HDR-images. Shannon Entropy provides a good objective measure of quality for colour and grey HDR images, suggesting that entropy can be used in automated HDR quality control assessment schemes.

This work will be discussed in Chapter 3.

Q3) Can the quality of a Tone-mapped HDR image be assessed using electroencephalography?

To answer this question, we investigated the relationship between changes in EEG features and subjective quality test scores (i.e. MOS) for HDR images viewed with a mobile device. Features of EEG are the EEG activities, (i.e. alpha, beta, theta, and delta). EEG activities are generally classified according to their frequency, amplitude, and shape, as well as the sites on the scalp at which they are recorded. While changes in EEG represent a response to something such as, opening and closing eyes.

The results show that changes in the gamma and beta bands correlated negatively with MOS, whereas positive correlations were observed in the alpha band. Coupling between activities in the delta and beta bands, (i.e. a positive correlation between power in the fast beta and slow delta frequency bands) was related to anxiety and dissatisfaction. The results therefore suggest that increases in the degree of coupling are associated with decreases in HDR quality. This also suggests that human emotions play a significant role in the assessment of QoE of HDR images.

These findings can potentially be exploited in objective QoE perception modelling.

This work will be discussed in Chapter 4.

Q4) Can the QoE of Tone-mapped HDR images be predicted?

This work is based on the results for the previous research question, which suggested that coupling between delta and beta frequency bands can be used to characterise human emotions such as anxiety and dissatisfaction. The proposed model can predict user acceptability and satisfaction in various mobile HDR image scenarios based on delta-beta coupling. A good/bad QoE evaluation is related to positive/negative emotions. Moreover, a stimulus, i.e. Multimedia content might cause an emotion at the recipient due to its meaning. These two factors may affect Mean Opinion Score (MOS) Prediction [38], [49].

HDR image quality was predicted in terms of the MOS. Subjective quality tests were conducted to develop and evaluate the model. In terms of performance, the model exhibited strong predictive accuracy of at least 82%.

This work will be discussed in Chapter 5.

Q5) Can colour vision deficiency (CVD) be detected using EEG and HDR images?

We hypothesised that EEG and HDR images can potentially be used to provide a low-cost, simple, and rapid method to detect CVD in both adults and younger children. An EEG measures the electrical activity of the brain, is non-invasive, low-cost, has a high temporal resolution, and provides valuable information about brain dynamics. HDR images represent a wide range of luminance levels and produce realistic and visually appealing content that can represent the different shades of colour and amount of light in the images. When HDR images are viewed and participants assess image quality, changes in the EEG may be evident that are associated with CVD. Features of EEG are the EEG activities (i.e., alpha, beta, theta, and delta). EEG activities are generally classified according to their frequency, amplitude, and shape, as well as the sites on the scalp at which they are recorded. The most familiar classification uses EEG frequency bands. While changes in EEG represent a response to something such as, opening and closing eyes [23], [50].

Using the model, the results show we were able to detect CVD with a sensitivity and specificity of up to 100%. This suggests that it may be possible to develop a reliable method of detecting CVD using EEG and HDR images, However, the number of subjects is relatively small; the results are need to be confirmed by much larger dataset for subjects.

This work will be discussed in Chapter 6.

Q6) Can HDR imaging techniques be used to enhance the quality of poor dental images so that they are acceptable for clinical use?

Radiographic images awarded grade 2 and 3 (the grade given to the quality of the image irrespective of any technical issues) were randomly selected from the SOELHealth database. SOEL Health is a dental software system and provides a cumulative total of clinical activity provided by dental students for the period in

Plymouth University Peninsula Schools of Medicine & Dentistry (PUPSMD) [51]. These radiographs were then modified using different HDR techniques. Fully blinded, seven dental professionals from the Peninsula Dental School at the University of Plymouth were asked to grade both the original and modified images. The results show that, from one poor LDR radiographic image, I increased the quality of the images that were processed. The objectives of turning a grade 3 image into a grade 2 image and a grade 2 image into a grade 1 image has been achieved. This eliminates the need for additional patient exposure to x-ray radiation when the quality of dental images is poor. This work will be discussed in Chapter 7.

1.3. Aim and objectives

The main aim of this thesis was to assess the QoE of HDR images using a physiological method and investigate potential applications for this method in healthcare. Although several TMOs have been proposed [52]-[55], few visual experiments have been conducted to evaluate the performance of TM algorithms for the end-user under normal viewing conditions with the aim of delivering a better QoE. Moreover, a sound testing and evaluation methodology based on psychophysical experimental results has yet to be established [1], [37].

The objectives of the thesis are:

- To investigate the impact of TMOs on the Quality of Experience of HDR images for SSDs of different sizes and resolutions.
- To investigate the impact of tone-mapping operators and viewing devices on the visual quality of experience of colour and greyscale HDR images.
- To develop a model to predict QoE when viewing HDR images on SSDs.
- To investigate the changes in brain activities during HDR image quality assessment, and to understand if these changes are related to HDR image quality perception in terms of QoE. Then using the outcome to enhance the QoE model and gain a deeper insight into QoE for SSDs.

- To investigate the relationship between changes in the EEG of CVD patients when viewing HDR images with SSD. Moreover, to propose a new method to detect CVD from EEG and HDR images. The changes in brain activity have been invoked, due to CVD by showing HDR images to participants.
- To explore the use of HDR image enhancement techniques and routinely collect NHS radiographic data to minimise the exposure of patients to additional radiation and improve patient care. This will also facilitate quality assurance (QA) monitoring of x-ray images in clinical dentistry, [56], [57]. QA is a plan of action, concern and responsibility to ensure that the x-ray images obtained in a dental practice are of the highest standard, with minimal exposure to the patients and dental staff and resulting in the maximum diagnostic yield Improving the quality of dental x-ray images. Without re-exposing patients to ionising radiation, would enhance the diagnostic power of radiographs and improve patient care[48], [31].

1.4. Contributions of the thesis

The main contributions of the thesis are as follows:

1. A critical review of relevant literature on HDR methods, techniques and applications was conducted to gain knowledge and insight into key HDR imaging issues.
2. A detailed understanding of the relationship between the most popular TMOs and viewing devices using subjective and objective methods. Different mobile displays and resolutions were presented under normal viewing conditions for the end-user with the LDR display as a reference. The results show that,

compared to computer displays, SSDs have an impact on the performance of TMOs.

3. A critical investigation of the impact of TMOs for different displays and devices, and QoE resolutions for both coloured and greyscale HDR images. I found that the higher the resolution, the better the HDR-image quality. Surprisingly, there was no significant difference between the scores for colour and grey images in SSDs. Thus, the device and TMOs have an equal effect on QoE for both colour and grey HDR-images. Shannon Entropy provided a good objective measure of quality for colour and grey HDR images, suggesting that entropy can be used in automated HDR quality control assessment schemes.
4. A novel electrophysiology-based QoE assessment of HDR images has been proposed, that can be used to predict perceived image quality by investigating the relationship between changes in EEG features and the subjective quality of HDR images. Previous studies have shown that physiological measurements provide valuable insights into the QoE of advanced media technologies. In this work0, the correlation between the mean power in the delta and beta bands was used as a measure of coupling between the activities in these bands. This is linked to negative behavioural characteristics (e.g. anxiety, frustration, dissatisfaction). Our research is based on clinical findings [12-16] that suggest that increased EEG delta-beta coupling promotes behavioural inhibition states. Thus, increases in the degree of coupling are associated with decreases in HDR quality. This has not previously been applied in electrophysiology-based QoE assessments of HDR image quality. This approach may therefore provide an insight into human preferences and perceptions about a service or product and hence user-perceived quality.
5. Developing an EEG-Based QoE model of human behaviour for High Dynamic Range Images. Motivated by the promising insights identified in point 4[], the

collected dataset have been used to identify and highlight the main challenges, by using a novel process to collect user acceptance data through an iPhone and applied a nonlinear regression technique to produce mathematical QoE content dependent models that predict acceptability based on the nature of the data fit curve. Then the statistical technique have been adopted to find QoE models that can generate the best-fitting estimate of the true acceptability curves.

6. A new method of detecting CVD have been proposed from EEG and HDR images. Then investigated the relationships between changes in the EEG of CVD patients when viewing HDR images and SSD by invoking changes in brain activity.
7. A method have been developed to enhance poor dental radiographic images using only one HDR image. This finding will minimise exposure to additional radiation and improve patient care. It will also facilitate QA monitoring of x-ray images in clinical dentistry.

1.5. Outline of thesis

The thesis is organised as follows:

A brief background information on the High Dynamic Range Imaging is explained in chapter 2, with a detailed description of the quality of experience and the use of neurophysiology in multimedia quality perception. Section 2.1 gives the background on HDR imaging with a comparison of HDR images with traditional images, and HDR imaging pipeline. Section 2.2 explains briefly the tone-mapping operators evaluated in the study. Section 2.3 explains the quality of experience in tone-mapped images. Section 2.4 describes the neurophysiology in multimedia quality perception. Section 2.5 is the chapter summary.

Chapter 3 discusses the impact of tone-mapping operators and viewing devices on the visual quality of experience of colour and greyscale HDR images. Section 3.1 is the chapter introduction. Section 3.2 explains the experiment methodology for both Subjective and objective assessment of the impact of TMOs and viewing devices. Section 3.3 discusses the subjective and objective results. Section 3.4 is the chapter's discussion and finally, Section 3.5 is the summary.

Chapter 4 investigates the relationships between changes in EEG features and subjective quality of HDR images. Section 4.1 is the introduction to the chapter. Section 4.2 is the related work in both EEG and delta-beta coupling. Section 4.3 explains the data collection of the experiment; it includes participants, ethics, test stimuli, EEG signal acquisition, test setup and methodology, pre-processing and feature extraction. Section 4.4 explains the results of subjective rating analysis, EEG signal analysis, correlation and the coupling measurements. Finally, the chapter summary is given in Section 4.5.

Chapter 5 describes the proposed EEG-Based QoE Model of Human Behaviour for Mobile High Dynamic Range Images. Section 5.1 is the Chapter 5 introduction, Section 5.2 is the related work. The data collection is explained in Section 5.3. In Section 5.4 the mobile EEG-based QoE, model and its evaluation are described. Finally, the chapter is summarised in Section 5.5.

Chapter 6 explains the new method to detect colour vision deficiency using the EEG and high dynamic range images. Section 6.1 is the introduction to the chapter; Section 6.2 describes the investigation of the relationships between changes in the EEG and CVD. The results of this are presented in Section 6.3. In Section 6.4, the proposed new approach for the detection of CVD condition is presented and includes the p-value analysis and model development. Section 6.5 discusses the results and findings, and finally, the summary is in Section 6.6.

Chapter 7 presents a pilot study on enhancing the quality of dental X-ray images to reduce patient radiation exposure and improve diagnoses. Section 7.1 introduces the problems; Section 7.2 presents the TMOs used in this study. Section 7.3 describes the material and methods, Section 7.4 presents the results, and Section 7.5 is the discussion. Finally, the Section 7.5 summarises chapter.

Chapter 8 is the final chapter of the thesis. Section 8.1 is the introduction to the chapter. Section 8.2 highlights the main contribution to knowledge. Section 8.3 highlights the limitations of the current work and in Section 8.4; suggestion for future work is presented. Finally, Section 8.5 concludes the Chapter.

Chapter 2 Background

2.1 Introduction

The field of high-dynamic-range imaging is rapidly maturing with improved image capture techniques, graphics algorithms' ability to produce arbitrarily large dynamic ranges, and emerging standards in high-dynamic-range file formats, due to its ability to capture a wide range of luminance values, similar to that of the human visual system (HVS). However, current monitor technology imposes severe constraints on the range of luminance values that can be displayed. Although HDR monitors will be more widely available in the near future, currently they are still costly. Therefore, to prepare HDR images for display on conventional display devices, we must bring the range of values to a displayable range, a process called tone reproduction or tone mapping [58].

A vital component in the HDR imaging pipeline is tone mapping. The purpose of tone mapping is to adapt the final HDR content for viewing on a display device that is limited in terms of dynamic range and colour gamut. Methods for tone mapping started to appear in the early 1990s, and have since evolved rapidly with a vast number of tone-mapping operators (TMOs) introduced in the literature[59].

A number of different TM methods (operators) have been proposed in the past two decades [1, 2]. However, also due to their sheer number, the advantages and disadvantages of these methods are not immanently clear, and therefore a thorough and systematic is highly desirable [59].

There are two separate approaches to acquire HDR images, namely hardware and software approaches [1]. The hardware approach tries to resolve it in the image acquisition pipeline of the digital cameras. The digital cameras have been improved in terms of quality and performance yet; photography is still having difficulties with storing and displaying the wide range of radiance variations in the real world. The scenes in the real world comprise of harsh lightening conditions that cause shadows (underexposed regions) or highlights (overexposed regions) in digitally captured images. The reason is that the dynamic range of sensors of the camera is not high enough for capturing the overall dynamic range. For this reason, camera sensors, which have the ability to capture a wide dynamic range, have been developed [3]. On the other hand, most of the cameras and monitors are LDR, so there is a need to find a way to use the LDR devices to get the HDR images[1], [3], [55], [62], [23], [24].

In the software approach, the problem had been defined by post-processing techniques. Since the hardware, solutions are considered expensive and need advance developments in this field, which are not preferred, by companies or researchers. The software solutions are easy, inexpensive compared to the hardware solutions and generally independent of hardware platforms[3], [63]–[65].

The solution to capture a high dynamic range scene with a limited dynamic range device is to split the full dynamic range into smaller sections. By means of this, the full dynamic range is represented by low dynamic range images. These technologies are called tone mapping or tone reproduction [2] [55], [62], [64], [66]. Different TMOs create different tone mapped images, and a natural question is which one has the best quality. Several studies have been done so far to evaluate TMOs subjectively and objectively [37], [54], [55], [67]–[70].

2.2 Comparison of HDR images with traditional images (LDR)

A high dynamic range image can describe a greater range of colour and brightness than can be represented in a low dynamic range (LDR) image. While a standard LDR image typically uses 8 bits to store each colour of a pixel, an HDR image is most often specified to floating point precision. The difference makes it possible to encode the entire range of colours and luminance visible to the human eye [3] [4] [59]. Floating-point values can represent values between integers, moreover, because of the scaling factor; they can represent a much greater range of values. On the other hand, floating-point operations usually are slightly slower than integer operations [71].

The luminance of the high dynamic range image in the real world vary from 10^4 cd/m^2 to10^6 cd/m² and can be stored as floating point values[3], [4]. On the other hand, the low dynamic range (LDR) of images/videos store the intensities of the scene as integer pixel values, normally in the range [0 255] which represent colours that should appear on a display device (see Figure 2-1) and not necessarily correspond to the scene intensities[3] [62]. According to this, the areas that are too dark are clipped to black (0) and areas that are too bright are clipped to white (255). Undoubtedly, this will lead to losses in both contrast and visual details. The representation of floating point in HDR overcomes this; instead of the bright and dark areas being saturated in an ad-hoc manner as is the case with LDR, they are assigned values proportional to the actual scene intensity [55], [60], [62]. Therefore, HDR content is scene-referred; as a result, an HDR still image can capture very high contrasts, which in turn permits it to incorporate details that the human eye can recognize.

Although HDR imaging offers recognizable advantages over the traditional LDR content in terms of enhanced visual quality of experience (QoE), its large-scale deployment at consumer levels is severely held back due to two major issues [72], [15]. The first one stems from the certainty that an HDR file requires larger storage space in comparison to an LDR file. For instance, an HDR still image may occupy 4 times the needed space for an LDR version of the same image [3]. Thus, as a result, effective compression algorithms are needed for HDR images/video. It should be noted that compression of LDR content has been a keen research area in any case and the occurrence of HDR images provides an additional impetus to this field. The second issue is that HDR content cannot be directly displayed on traditional display devices as these cannot provide the required luminance range, which is needed [62].

HDR image rendering algorithms can be generally classified according to the spatial processing techniques into two categories: global and local operators [3], [52], [73]-[75], [76]. The global operator applies the same transformation to every pixel in the image based on the global image content, while for local operators a specific mapping approach is used for every pixel according to its spatially localized content [18], [19]. It is significant to stress that in global operators, for every image it is unnecessary for the same operator applied congruently, such as the histogram; the global operator can be a function of image information. Furthermore, the local operators take various approaches to determine the spatial extent of the operator, for example, low-pass filters, edge-preserving low-pass filters, or multi-scale pyramids [54].

In both the global and local tone-mapping approaches, there are strengths and weaknesses. The global operators have a tendency to be computationally simple and as a result can be easy to perform and faster to implement. The spatial processing of the local operators tends to be computationally more expensive but can permit for a considerable reduction in the general dynamic range [55], [75].

In other hand, processing, an HDR image only globally can lead to losing contrast, which is clearly making a loss in the visibility of detail. Local operators allow increasing the local contrast, which increases the visibility of several parts of the image whereas the global dynamic range Scales the dynamic range of the image to the output devices [15], [16].

The choice of the best tone-mapping operator, weather it is global or local depends on the content, display type and size, and other environmental parameters such as back lit lighting, environment illumination, etc. These parameters (context and content) need to be explicitly taken into account when building a support for HDR images in existing LDR-based applications and display systems [60] [62] [78][6].

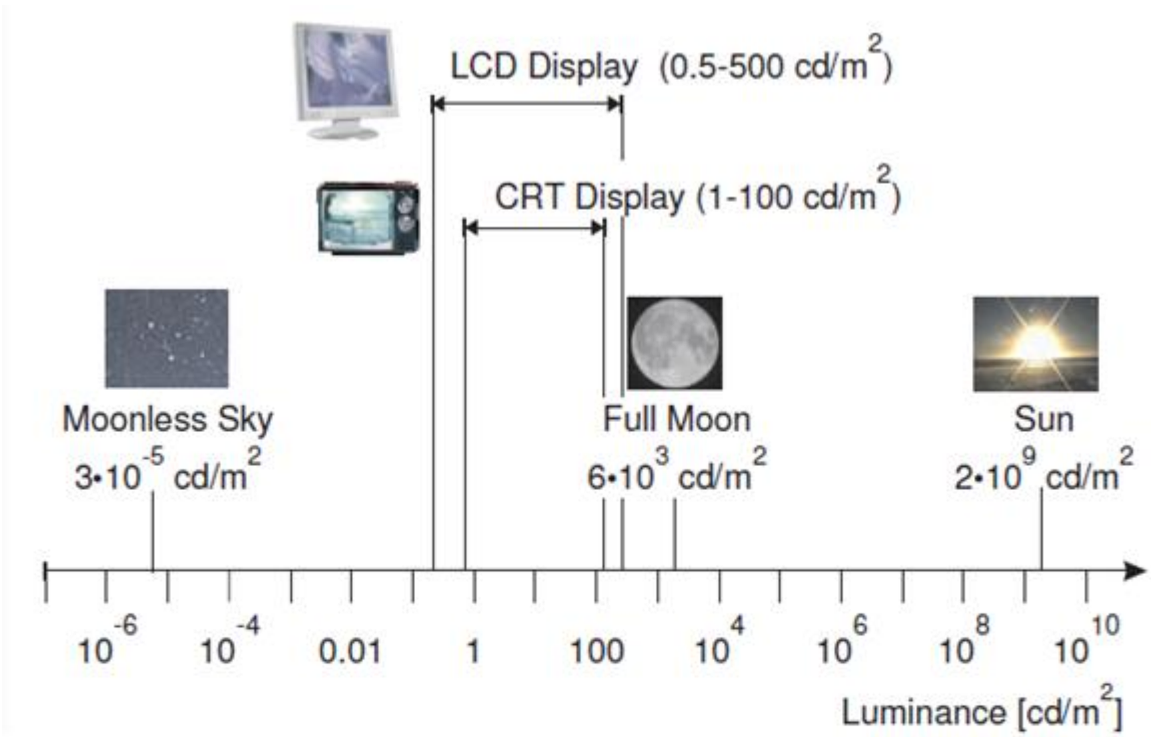


Figure 2-1: Real-world luminance values compared with the range of luminance that can be displayed on CRT and LDR monitors.

2.3 High dynamic range imaging pipeline

Values of physically correct light can be captured and fully processed for several applications with no need to signal linearizing and to dealing with clamped values. The very bright and dark areas of a scene can be recorded all at once into an image or a video, averting over-exposed and under-exposed areas. Methods of traditional imaging do not use physical values and normally are constrained by limitations in technology that could handle only an 8-bit per colour channel per pixel. This imagery (8-bit or less per colour channel) points out to LDR imagery.

This change in recording the light can be compared to the introduction of colour photography and has changed each stage of the imaging pipeline, see Figure 2-2. The three main stages for High Dynamic Range imaging pipeline are: capturing, storing, and displaying [4] [61], [79].

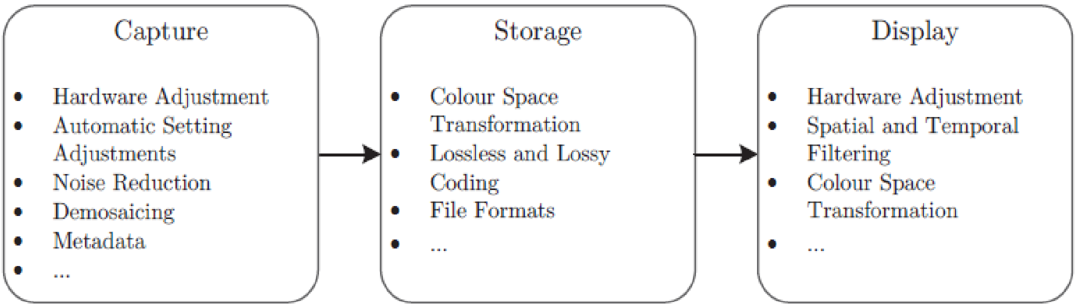


Figure 2-2: The pipeline of the digital imaging represents the stages through which images and videos pass from capture to display.

Multiple exposure images are captured and combined to obtain an HDR image. In the HDR imaging, several images are taken under different exposures. Those images usually have displacement from one another due to camera and/or object motions. The challenge of the super HDR imaging is to align those images because any image contains ”lost” regions where texture information is completely lost due to overexposure or underexposure[80]. First of all the images are taken from various exposures through the camera features or by exploiting natural climatic conditions while capturing images. The one of the images is selected as main image. For every other image, in the main image the displacement regions are found. Moreover for all images occlusions and blur regions are found[81], [82]. Then this image is quantized, compressed, and stored. Additional processing can be applied to the image. For example, high luminance areas in the synthetic object can be extracted and used to re-light them. Eventually, the HDR image or processed ones can be visualized using traditional LDR display technologies or native HDR monitors [3], [4], [64]

2.3.1 Capturing

The consumer cameras that are currently available can only capture 8-bit images or 12-bit images in a RAW format which does not cover the full dynamic range of irradiance values in most real-world locations [2] [3]. The main problem with film and digital cameras is that they do not exhibit a linear response, but a more general function called Camera Response Function (CRF). In the commercial field, numerous companies provide HDR cameras based on the technique of capturing automatic multiple exposures. The two leading cameras are the Spheron HDR VR camera designed by Spheron VR GmbH and the Panoscan MK-3 designed by Panoscan Ltd, both of which are full 360-degree panoramic cameras at high resolution.

Resolution is the number of pixels (individual points of colour) contained on a display monitor, expressed in terms of the number of pixels on the horizontal axis and the number on the vertical axis. The sharpness of the image on a display depends on the resolution and the size of the monitor. The same pixel resolution will be sharper on a smaller monitor and gradually lose sharpness on larger monitors because the same number of pixels are being spread out over a larger number of inches [67].

In the cinema industry, some companies have offered high-quality solutions such as the Viper camera produced by Thomson GV, the Phantom HD camera produced by Vision Research, and the Red One camera produced by RED Company. All these video cameras offer high frame rates, full high definition (1,920 × 1,080) resolution, low noise, a good dynamic range (equivalent to the range of celluloid film), and a 10/12-bit per channel in the logarithmic/linear domain. Nevertheless, they are extremely expensive, sometimes they are only available for rental, and they do not comprise the full dynamic range of the HVS [3].

2.3.2 Storing

An uncompressed HDR image usually requires 96 bits per pixels (bpp), which is four times the amount of an uncompressed LDR image. This is because an uncompressed HDR colour channel is usually encoded the same way as a single precision floating point. Digital camera images are usually stored in 24-bit JPEG format with separate eight-bit channels for red, green, and blue. This results in a resolution of 28 = 256 for each channel or 28 x 28 x 28 = 16 million discreet values in total. Although 16 million colours may seem large, each channel can only display 256 discrete values. Using the RAW image format for image capture, which is typically 12 bits or 212 = 4096 discrete values per channel, may increase the number of discrete values. However, a different file format is needed to represent the complete dynamic range of the human visual system [83], [84]. Several file formats have been developed to overcome the dynamic range limitations of the classical JPEG format commonly used as output by digital cameras. These all differ in terms of the resulting file size and the dynamic range they are able to describe [3], [61] [85].

Portable Float Map

The Portable Float Map HDRI format, which is like a floating-point TIFF, assigns 4 bytes to each of the channels; one for the sign, one for the exponent, and the other two to the mantissa [79][49].

Radiance RGBE

The most commonly used HDR image format was developed by Greg Ward [86] for the radiance synthetic rendering system. Each pixel is represented by a Mantissa for each channel and a common exponent. They are stored as 8-bit floating-point values, adding up to 32 bits per pixel. The dynamic range of the RGBE format is 76 orders of magnitude. Generally the Radiance format is recommended when saving an HDR file because it preserves the greatest dynamic range without excessive file bloating.[87].

Open EXR

This format is an open-source high-dynamic-range image file format that was developed by Industrial Light & Magic in 1999; the Open EXR file format is now used for all film production. It offers a higher dynamic range and supports lossless data compression and colour precision compared to the existing 8-bit or 10-bit image formats. The Open EXR format provides support for 16-bit floating-point, 32-bit floating-point, and 32-bit integer pixels [71].

JPEG-HDR

Is based on Dolby JPEG-HDR format, created in 2005 by Greg Ward [87] from BrightSide Technologies and Maryann Simmons from Walt Disney Feature Animation as a way to store high dynamic range images inside a standard JPEG file. The image encoding is based on two-layer RGBE image format used by Radiance renderer, both of which were also created by Ward. Reduction in file size is achieved by first converting the image into a tone-mapped version, then storing a reconstructive multiplier image in the same JPEG/JFIF file. Ordinary viewing software will ignore the multiplier image, allowing anyone to see the tone mapped version of the image presented in a standard dynamic range and colour gamut [44] [45].

PFS (Portable Floatmap Stream)

PFS is a raster image file format associated with the *pfstools* software. It supports high dynamic range images. It is an uncompressed format, primarily intended for temporary files and data streams [79], [83].

To conclude, HDR formats have been designed to cover the abilities of human vision, making them independent from the process of display and therefore appropriate for future use [85]. Despite the existence of efficient formats for HDR storage, there is a need for developing techniques for further HDR compression. This is because even with the HDR formats there is a huge memory requirement. Consequently, HDR content stored in a standard HDR format should be compressed further to enable development that is more practical and real-time processing. Therefore, there is need for research into effective HDR compression schemes and this therefore has been an important research area. A crucial and related issue is that the existing coding architectures have become widely adopted standards supported by almost all software and hardware equipment dealing with digital imaging. As a result, it will be of great interest to design HDR compression schemes that are compatible with existing coding architectures [72].

2.3.3 Displaying

A considerable number of the display devices now commercially available are unable to display the content of HDR images. This is because the current display technology has a contrast ratio of approximately 1,000:1, which is low; while a modern TFT flat, panel screen achieves a dynamic range of 300:1. This can be increased by up to 5000:1 for digital video projectors, although the display devices can process only 8/10-bit images for each colour channel. However, the maximum contrast of paper printer is relatively low at approximately 100:1. To optimise HDR images and display them so that neither the dark regions nor the highlights are clipped, new display technology is required. This display achieves a maximum luminance of approximately 3000 cd/m^2. Combined with a black value of only 0.015 cd/m^2, the total contrast ratio can be as high as 200,000:1 [1] [2] [51].

The progress in HDR display technology led to various experiments aimed at understanding how to best utilize the emerging HDR display devices. To this end two main types of studies have appeared. The first type investigates the advantages of HDR displays in conveying enhanced realism and visual quality. The second type of studies focuses on what to do with the enormous volume of existing LDR material. The problem here is to discover what sort of image processing best prepares LDR content for display on an HDR display device [60] [89].

Even though the HDR display technology is available, it is yet to reach consumer levels. In such scenario, the only alternative is to display HDR contents directly on commonly available devices such as CRT, LCD monitors, etc., which have a significantly low dynamic range. It follows that these cannot provide the necessary luminance range for a true HDR experience. Additionally, their contrast ratio is not good enough for displaying HDR contents. Therefore, an important issue in HDRI is to reduce the dynamic range of the HDR content. This problem has been commonly addressed by employing TMOs. It is also important to highlight that even the HDR displays cannot reach the luminance levels found in real world and some kind of tone mapping is needed before display the signal [62], [72].

2.4 Tone mapping operators

Several TMOs have been developed over the past few years. Some are simple and based on operations such as linear scaling and clipping while TMOS that are more sophisticated exploit several properties of the HVS with the aim of preserving the detail. However, TMOs usually lead to information loss, which can reduce the perceptual quality of the tone-mapped contents. This is to be expected as dynamic range compression invariably tends to destroy important details and textures, and can introduce additional artefacts related to changes in contrast and brightness [1]-[4] [42]. As mentioned in the previous section, TMOs can be broadly classified into two categories: local operators and global operators.

Chiu et al. [90] developed one of the first local TMOs by employing a local intensity function based on a low-pass filter to scale the local pixel values. In contrast, the method proposed by Fattal et al. [91] was based on compressing the magnitudes of large gradients and solving the Poisson equation on the modified gradient field to obtain tone mapped images. Durand et al. [65] developed a TMO based on the assumption that an HDR image can be decomposed into a base image and a detailed image. The contrast of the base layer is reduced using an edge-preserving filter (known as the bilateral filter). The tone-mapped image is obtained by multiplying the contrast-reduced base layer with the detailed image. Drago et al. [74] used logarithmic compression of the luminance values to reduce the dynamic range in HDR images. They used varying logarithmic bases to preserve local details and contrast.

The TMO proposed by Ashikimin [92] first estimates the local adaptation luminance at each point; this is then compressed using a simple mapping function. In the second stage, details lost in the first stage are re-introduced to obtain the final tone-mapped image. Reinhard et al. applied [93] the dodging and burning technique (traditionally used in photography) for dynamic range compression. A TMO based on a perceptual framework for contrast processing in HDR images was then introduced by Mantiuk et al.[79]. This operator involves the transformation of an image from luminance to a pyramid of low-pass contrast images and then to the visual response space. Mantiuk et al. claimed that, in this framework, dynamic range reduction could be achieved through simple scaling of the input.

A TMO known as iCAM06 [52] has also been developed. This is based on the sophisticated image colour appearance model (iCAM) and incorporates the spatial processing models in the HVS for contrast enhancement and photoreceptor light adaptation functions that enhance local details in highlights and shadows. Regarding global TMOs, the simplest of these is the linear operation in which the maximum input luminance is mapped to the maximum output value (the maximum luminance mapping) or the average luminance mapping (i.e. mapping average input luminance to the average output value). Another global TMO proposed by Ward [86] focuses on the preservation of perceived contrast. In this method, the scaling factor is derived from a psychophysical contrast sensitivity model. Tumblin et al. [94] developed a TMO based on the assumption that a real-world observer should be the same as a display observer. These are just some of the existing TMOs; however, the list is by no means exhaustive.

Although global TMOs preserve the overall contrast, they usually lose local details. Nevertheless, global operators are generally more computationally efficient than local ones, which is a significant advantage. Both local and global TMOs therefore have their own advantages and disadvantages. Because tone mapping reduces the dynamic range, it will invariably lead to a loss of visual details and affect the perceived HDR content [8] [30] [57]. Given that tone mapping is often required at different stages of the HDR pipeline (e.g. for compression and visualisation), it is important to analyse how they affect the visual experience of the processed HDR content. However, evaluating the overall HDR viewing experience is not an easy task because it is a multi-dimensional phenomenon.

2.4.1 Tone-mapping operators evaluated in the study

In this section the main methods which were proposed for displaying HDR images will be discussed, these operators heterogeneous from a simple linear scaling factor to further comprehensive high-end solutions, which take into account attributes of complex perceptual in-human. In other words, from unpretentious global (spatially uniform) mapping in complex multi-scale local (spatially varying) mapping, this is attempting to simulate the human visual system. With all cases, before displaying the image, an inverse display characterization was applied at the end of each operator to account nonlinearity of the inherent device. To be exact, the digital values in the original images were taken into account as values of linear magnitude [36]. We obviously understand that some of the operators' performance could be improved by modifying various parameters, but I've attempted to use their default settings as presented in the respective papers. Each of the ten main algorithms is briefly described in Table 2-1:

Table 2-1: Evaluated tone-mapping methods

TMO	Abbreviation	Method description	Process
Ashikhmin [92]	*AL1*	A tone mapping algorithm for high contrast images, the method takes into account two basic characteristics of the HVS: signalling absolute brightness and local contrast.	Local
Ferwerda [95]	*AL2*	This operator is based on a model of visual adaptation from psychophysical experiments that considered various aspects of the HVS such as visibility, visual acuity, and illumination change adaptation.	Local
Adaptive Logarithmic Mapping [76]	*AL3*	This is a fast algorithm suitable for interactive applications, which automatically produces realistic looking images for a wide variation of scenes exhibiting a high dynamic range of luminance.	Global

iCAM06 [53]	*AL4*	Modified ICAM operator, which is based on the physiology of the human's eye photoreceptors. The output of the operator is a combination of a locally adapted value around each pixel of the image and a globally adapted value based on the image averages.	Local
Fattal [91]	*AL5*	Compressing the gradient of the image luminance component and then constructing the LDR image by solving a Poisson equation on the compressed gradient image. The method is able to significantly enhance ordinary images by bringing out detail in dark regions.	Gradient Domain/ Local
Pattanaik [54], [96]	*AL6*	This is a new time-dependent tone-mapping operator, which is based on psychophysical experiments and a photoreceptor model for luminance values. This algorithm briefly can be decomposed into two models: the visual adaptation model and the visual appearance model.	Global
Photographic Reproduction [93]	*AL7*	This is based upon dodging-and-burning in traditional photography. It automatically applies various scales for luminance mapping to the prorated regions of highlights and shadows, where the local contrast is estimated using a centre--surround function with different spatial extent.	Global
Tumblin – Rushmeier [97]	*AL8*	They developed a tone reproduction operator that preserves brightness relationships, by using a psychophysical model of brightness perception.	Global
Ward [87]	*AL9*	A visibility matching tone reproduction operator for HDR scenes	Global
Bilateral Filtering [65]	*AL10*	Fast bilateral filtering for the display of HDR images conserving local details in the image. They argued that an image may be thought of as being composed of an HDR component for low frequencies and an LDR component with a high spatial frequency.	Frequency domain

2.4.2 Tone mapping and visual quality

There have been several studies related to how TMOs affect the visual quality of the tone-mapped content. We first briefly describe some of the existing studies related to the subjective evaluation of TMOs. The psychophysical experiments carried out by Drago et al. [74] aimed to evaluate six TMOs with regard to similarity and preference. Three perceptual attributes, namely apparent image contrast, apparent level of detail (visibility of scene features), and apparent naturalness (the degree to which the image resembled a realistic scene) were investigated. It was found that naturalness and details are important attributes for the perceptual evaluation of TMOs. The study by Kuang et al. [96] performed a series of three experiments. The first one aimed to test the performance of TMOs with regard to image preference. For this experiment, 12 HDR images were tone mapped using six different TMOs and evaluation was done using the paired comparison methodology. The second experiment dealt with the criteria (or attributes) observers used to scale image preference. The attributes that were investigated included highlight details, shadow details, overall contrast, sharpness, colourfulness, and the appearance of artefacts.

The subsequent regression analysis showed that the rating scale of a single image appearance attribute is often capable of predicting the overall preference. The third experiment was designed to evaluate HDR rendering algorithms for their perceptual accuracy of reproducing the appearance of real-world scenes. To that end, a direct comparison between three HDR real-world scenes and their corresponding rendered images displayed on a low dynamic-range LCD monitor was employed [52], [54], [96].

Yoshida et al. [73] conducted psychophysical experiments which involved the comparison between two real-world scenes and their corresponding tone mapped images (obtained by applying 7 different TMOs to the HDR images of those scenes). Similar to other studies, this one was also aimed at assessing the differences in how tone mapped images are perceived by human observers and was based on four attributes: image naturalness, overall contrast, overall brightness, and detail reproduction in dark and bright image regions.

Psychophysical experiments have traditionally used three methods for testing subjects' perception in stimulus detection and difference detection experiments: the method of limits, the method of constant stimuli and the method of adjustment [37].

In the ascending method of limits, some property of the stimulus starts out at a level so low that the stimulus could not be detected, and then this level is gradually increased until the participant reports that they are aware of it. In the method of constant stimuli, Instead of being presented in ascending or descending order, in the method of constant stimuli, the levels of a certain property of the stimulus are not related from one trial to the next, but presented randomly. This prevents the subject from being able to predict the level of the next stimulus, and therefore reduces errors of habituation and expectation. The method of adjustment asks the subject to control the level of the stimulus, instructs them to alter it until it is just barely detectable against the background noise, or is the same as the level of another stimulus. This is also called the method of average error. In this method the observer himself controls the magnitude of the variable stimulus beginning with a variable that is distinctly greater or lesser than a standard one and he varies it until he is satisfied by the subjectivity of two. [1], [39], [41]

In the experiments conducted by Ledda et al. [98], the subjects were presented three images at a time: the reference HDR image displayed on an HDR display and two-tone mapped images viewed on LCD monitors. They had to choose the image closest to the reference. Because an HDR display was used, factors such as controlling screen resolution, dimensions, viewing distance and ambient lighting could be controlled. This is in contrast to using a real-world scene as a reference, which might introduce uncontrolled variables. The authors have also reported the statistical analysis of the subjective data with respect to the overall quality and to the reproduction of features and details. Different from the mentioned studies, Cadik et al [37]. adopted both a direct rating (with reference) comparison of the tone-mapped images to the real scenes, and a subjective ranking of the tone mapped images without a real reference.

They further derived an over-all image quality estimate by defining a relationship (based on multivariate linear regression) between the attributes: reproduction of brightness, colour, contrast, detail and visibility of artefacts. The analysis further revealed that contrast, colour and artefacts are the major contributing factors in the overall judgment of the perceptual quality. However, it was also argued that the effect of attributes such as brightness is indirectly incorporated through other attributes. Another conclusion from this study was that there was an agreement between the ranking (of two-tone mapped images) and rating (with respect to a real scene) experiments. In contrast to this last observation.

Ashikimin et al.[99] found that there were significant differences in subjective opinions depending on whether a real scene is used as a reference or not. A recent survey can be found in [100] that evaluated TMOs for HDR video. It should be emphasized that most of these studies ranked the TMOs based on the performance of the respective subjective either experiments or outlined the factors affecting the visual quality of the tone-mapped content.

However, it might be misleading to generalize the results from these studies since the number of HDR stimuli was limited. Nevertheless, all of them establish beyond doubt that tone mapping (both in still images and videos) tends to not only reduce the visual quality, but also affects the naturalness of the processed HDR content (in addition for video stimuli there could be visible temporal artefacts). Because the underlying philosophy of TMOs concerns with reducing their range, they inevitably saturate visual information leading to loss of details. Consequently, their use for HDR visualization calls for extreme care.

Ashikmin [92] and iCAM06 [52] TMOs seem to provide better visual details in the outdoor and indoor simultaneously. A related aspect in tone mapping is that of naturalness. While it is quite clear that the tone mapping reduces visual quality, how it affects naturalness remains an unanswered question. In fact, all the user studies described previously implicitly account for naturalness. This is because when human observers judge the visual quality of tone-mapped content, not only the presence or absence of visual details affects their choice but is also affected implicitly by the naturalness of the tone-mapped content. Naturalness is a subjective quality, which is difficult to be quantified. In the light of this, it is not surprising that most of the TMOs only focus on retaining detail and/or maintaining local and global contrast but do not consider naturalness for processing the HDR content [74], [101].

For instance, an over-enhanced tone mapped image might have a very large number of details, but can still have poor visual appearance due to being unnatural. Thus, I' have have provided a brief overview of the impact of one mapping on the visual quality of HDR content.

2.5 HDR quality of experience

QoE is defined as "the overall acceptability of an application or service, as perceived subjectively by the end-user" [102] or "the degree of delight or annoyance of the user of an application or service" [103]. It is closely related to but more user-centric than the traditional quality of service (QoS) that is rather device-, infrastructure-, and signal-centric, such as signal-to-noise ratio (SNR), delay, packet loss rate, etc. QoE of multimedia content is not only influenced by QoS, but also related to the characteristics of the human sensory systems such as Weber's law, no uniform auditory and visual sensitivity functions, and Just Noticeable Difference (JND) [104]. Moreover, HDR quality of experience is a rather wide term in that it can include several dimensions, including perceptual quality, naturalness, visual attention, aesthetic appeal and so on.

Of course, these are unnecessarily independent because of instance perceptual quality can implicitly account for naturalness. In the following, First, the differences between HDR and LDR have been outlined from the angle of viewing conditions and then introduced the reader to the topic of subjective and objective HDR quality assessment [11].

2.5.1 Subjective assessment of HDR quality

The human judgment of visual quality remains the gold standard as far the accuracy of quality prediction is concerned [9], [105]-[107]. HDR is no exception. However, as outlined in the previous section, a subjective measurement of HDR quality calls for more careful considerations of viewing conditions. Otherwise, the results may not accurately represent the actual perceived quality. Another important factor in the HDR subjective test design is the use of TMOs. They will not be used for visualization, but for HDR processing (e.g. compression). Therefore, it requires care to find TMO parameters when preparing HDR content for subjective evaluation [35], [73], [108].

Concerning the sources of distortions in HDR, the first is related to tone mapping. Another common distortion is compression related artefacts. Another category of specific artefacts that occur in HDR is those due to inverse tone mapping. The inverse tone-mapping is the final step in a typical backwards-compatible HDR compression pipeline and can cause saturation, excess or lack of contrast in the HDR scene. Thus, it can be highlighted that HDR processing includes specific distortion sources (that are not typically present in LDR regime) like tone mapping and inverse tone mapping in addition to common artefacts (due to compression, transmission, post-processing etc.) [100], [109], [110].

It is also interesting to note that distortions due to tone mapping and inverse tone mapping are not necessarily additive. That is, inverse tone mapping can offset some artefacts from tone mapping. Further, as explained in previous sections, visual attention can be significantly modified due to tone mapping and this can degrade the overall HDR viewing experience. Thus, HDR quality measurement is challenging in that the processed HDR content can suffer from multiple distortions (which need not be independent of each other). This, coupled with the fact that the high luminance in HDR can potentially amplify artefacts suggests that extra care needs to be taken for accurate subjective measurement of HDR quality.

Very few research efforts have been reported for subjective HDR quality assessment. The reasons for this are related to the requirement of specialized HDR displays and the unavailability of real HDR content [11], [35], [61], [111]. However, two recent studies have employed an HDR display for QoE evaluation. The first one [112] investigated into codec optimization criterion and perceptual quality issues in HDR. The second study [62] analysed the impact of TMOs in HDR compression. The conclusions from these studies revealed that, indeed, the perceptual quality of the decompressed HDR signal is dependent on the tone mapping method employed and statistical evidence were also presented to support that.

The final point about subjective HDR quality assessment is related to the need for specialized displays. As has already been pointed out, such HDR displays are still not common on a large scale (although this could change within a reasonable time-frame). In the light of such constraint, it is natural to ask if HDR quality measurement can be tackled with existing LDR set up (LDR displays, specifications etc.). Indeed, it is not absurd to think of tone mapping the HDR content and estimate its quality subjectively on an LDR monitor. However, it is fair to reiterate that even HDR displays have their own limitations (in particular due to the dual modulation process) and cannot fully represent HDR content.

2.5.2 Objective assessment of HDR quality

Objective quality measurement is the use of computational models to predict quality. An objective method for quality prediction is a useful tool in cases where subjective assessment is not feasible (such as real-time applications). Being a mathematical model, an objective method is more convenient to be deployed. However, objective methods cannot be as accurate as the subjective ones. Thus, one line of thinking in the research community has been towards developing more accurate objective methods. While this is reasonable, it is important to understand that the HVS represents a complex visual information processing system. Consequently, all the objective methods (for LDR and HDR) are merely approximations and they cannot be relied upon as a generic solution to quality prediction. Nonetheless, it is also important to highlight that objective method can achieve a reasonable prediction accuracy in the limited context of an application scenario. For example, the mean squared error (MSE) continues to be deployed extensively in visual data compression [37], [108], [111], [113]–[115].

Pertaining to LDR, one finds that a lot of research effort has been spent over the past decade. Most of it is devoted to the development of full-reference methods that require both the reference and processed visual signal for quality computations. In contrast, there exist very few methods for objective HDR quality prediction. The reasons for this are already outlined and related to different viewing conditions as compared to LDR. Thus, mathematical models of HVS's functioning (e.g. contrast sensitivity) used in LDR methods can no longer be effective for HDR. Another reason for the slow progress of objective HDR quality measurement can be attributed to the lack of standard databases.

The HDR-VDP-2 (High Dynamic Range-Visual Difference Predictor)[116] is a fairly recent and comprehensive method for objective measurement of HDR quality. It is an extension of the Visible Differences Predictor (VDP) algorithm. The HDR-VDP-2 uses an approximate model of the human visual system (HVS) derived from new contrast sensitivity measurements. Specifically, a customized contrast sensitivity function (CSF) was employed to cover a large luminance range as compared to the conventional CSFs. HDR-VDP-2 is essentially a visibility prediction metric. That is, it provides a 2D map with probabilities of detection at each pixel point and this is obviously related to the perceived quality because a higher detection probability implies a higher distortion level at the specified point. Nevertheless, in many cases, it is crucial to know an overall quality score (rather than just the local distortion visibility probability). Pooling is a crucial aspect in converting local error distribution into a single score that denotes the perceptual quality and the human visual system can very easily do that accurately. But it is much more difficult to realize that in an objective quality prediction model given the underlying complexities and lack of knowledge of the HVS's pooling mechanisms [115]-[117].

It is believed that multiple features jointly affect the HVSs perception of visual quality, and their relationship with the overall quality is possibly nonlinear and difficult to be determined a priori. Therefore, the approach that the HDR-VDP- takes is that finding the pooling parameters via optimization of correlation with subjective scores. In its original implementation, the authors of HDR-VDP-2 tried over 20 different combinations of aggregating (or pooling) functions. These included maximum values, percentiles (50, 75, and 95) and a range of power mean (normalized Minkowski summation) with the exponent ranging from 0.5 to 16. The aim was to maximize the value of Spearman's correlation coefficient in order to find the best pooling function and its parameters. While HDR-VDP-2 is a comprehensive method for HDR quality assessment, there is an issue concerning pooling in HDR-VDP-2. This relates to parameter optimization. That is, the parameters of the polling function in HDR-VDP-2 were found by maximizing (optimizing) correlation using existing LDR image databases. Therefore, its effectiveness in predicting the visual quality of HDR images is questionable given the different characteristics LDR and HDR images, especially in terms of distortion visibility and overall visual appeal [117].

2.6 Neurophysiology in multimedia quality perception

Neurophysiology is a medical specialty that studies the central and peripheral nervous systems through the recording of bioelectrical activity, whether spontaneous or stimulated. It encompasses both research regarding the pathophysiology along with clinical methods used to diagnose diseases involving both central and peripheral nervous systems [43], [118]. Examinations in the clinical neurophysiology field are not limited to tests conducted in a laboratory. It is thought of as an extension of a neurologic consultation. Tests that are conducted are concerned with measuring the electrical functions of the brain, spinal cord, and nerves in the limbs and muscles. In hospitals that possess clinical neurophysiology facilities, the major diagnostic modalities employed include: Electromyography, Electroencephalography, Evoked potentials and Polysomnography [108].In subjective quality tests, it can be determined which technical settings lead to an acceptable perceived quality. However, the ecological validity of the current subjective testing methodologies has been questioned [119]. Consequently, methods that could be used in the normal environment of the user, with as fewer interruptions as possible of the used service and preferable non-invasive towards the user, would be an ideal testing methodology [120].

Additionally, sometimes it is difficult for an observer to connect the level of experienced quality with the rating scale presented to them, and as a result, not all relevant responses can be collected using subjective ratings. This will require developing methods that can estimate quality by other means than explicitly asking the user [1] [11] [43]. Here, (neuro) physiological measures could be helpful to overcome these challenges as they can be taken directly and non-verbally from the observer [1]. Although these measures are more difficult to collect, they measure the response of the observer directly which may even detect subtle differences that are not perceptible on the level of behaviour, i.e. the level of the conscious opinion ratings[13]. Due to physical and chemical processes in the brain, electrical activity is being elicited that can be recorded from the scalp's surface using electrodes; for example, by an electroencephalogram (EEG) [15] [121] [122]. These electrical responses are directly due to neural activity and can be recorded at a very high temporal resolution. Consequently, early responses can be identified, in comparison with hemodynamic measures, which analyse changes in blood flow and which take a few seconds until a response can be recorded [123].

Using neurophysiological assessment in the QoE domain is rather young, and a limited number of researches have been conducted in this area [15], [41]. The basis for analysing neurophysiological reactions towards changes in the QoE in audio and speech signals has been performed in studies from Miettinen [124] and Antons [15], [123], [125]. Based on these fundamentals, studies that have been performed in the area of video and image quality assessment using mostly measures of EEG, but also different other physiological techniques, such as near-infrared spectroscopy or electrocardiogram[15], [43], [41], [10].

2.6.1 Electroencephalogram (EEG) in multimedia quality perception

The EEG measures voltage variation caused by neuron activity in the brain, it can be recorded by attaching electrodes to the scalp of a subject. Since its discovery by Berger [126] in 1929, it has become an extensively used method for investigating the physiological link between perceptual and attentional processes. This measure has a rather limited spatial resolution based on the fact that the brain is a wet conductor the signal recorded by one electrode is a mixture of all existent sources – but an excellent temporal resolution with a precision of milliseconds [19], [15], [85].

The analysis of EEG data can be performed in two different ways: Firstly, data can be analysed concerning a short and distinct event that elicits an Event-Related Potential (ERP). Here, the amplitude of the ERP's component can vary with the level of quality perceived by the user. Secondly, data can be studied using an analysis of the frequency band power. This is especially interesting when drawing conclusions about the mental state of participants, or to describe the change in the mental state between conditions [41], [40], [127].

Additionally, other unwanted information is recorded as well, e.g. voltage changes due to body movement, eye-movement and other unrelated signal sources. Due to the noise existent in the EEG signal, it is important to create sophisticated experimental setups. Clinical research guidelines for experimental designs already exist and carry important implications for research in the domain of QoE based on them [128]. The equipment that is used in EEG research usually is expensive and in the case of using wet electrodes also challenging to attach to the participant. Lately, new low-cost EEG devices have appeared on the market, such as the Emotiv-EPOC 1 and NeuroSky MindWave2 headsets. Though these consumer products are comparably low-priced and easy to attach, the data quality, i.e. noisiness of the signal and precision, using those products is less trustworthy to the devices used in clinical applications However, these products have shown to capture useful information in the context of QoE related research [11] [15].

In the continuous EEG, five main different frequency ranges are ascribed to specific states of the brain: delta band (1-4 Hz), theta band (4-8 Hz), alpha band (8-13 Hz), beta band (13-30 Hz) and the gamma band (36-44 Hz) [12], [127]. The delta band is present during deep sleep; the theta band occurs during light sleep and is an indicator of decreased alertness. Activity in the alpha band is related to relaxed wakefulness with eyes closed and a decrease in alertness. Beta and gamma band are ascribed to high arousal and focused attention [11], [12], [40].

2.6.2 Spectral analysis

Due to the possibility that more natural stimuli in terms of stimulus length can be used, it is possible to examine the effect of longer duration media stimuli on the recipients. Analysing the power in the before mentioned frequency bands is widely done in assessing the cognitive state of car drivers. In studies by Antons et al.[125], participants were exposed to high quality and low-quality sequences of longer auditory material. Their only task was to rate the content on a scale every few minutes, and for the rest of the time, they should focus on the presented content. Higher values in the alpha band power were observed when being exposed to low-quality stimuli compared to higher quality stimuli, which is ascribed to fatigue and impaired information processing [22].

Recently there also have been efforts to use EEG in the area of gaming QoE. Especially, while games are emerging that are run over the Internet, classical QoE problems (paired with additional problems) evolve. In [30], the authors measured varying alpha activity with different levels of video compression. In this study, participants played a first-person shooter game in a cloud gaming setup with varying levels of video quality caused by different video compression bit-rate. It was found that the video quality influenced the perceived quality, player experience, the subjective ratings and the alpha frequency band power. It is shown that physiological measures capture the influence on the player in terms of a reduced cognitive state.

2.7 Summary

HDR imaging is an emerging area within the realm of visual signal processing. It brings to those two major advantages over the traditional imaging systems. First, it can provide a more immersive and realistic viewing experience to the users. Second, the higher bit depth required in HDR will allow for more signal manipulation (eg. preprocessing towards efficient encoding) as compared to the traditional content. However, to exploit HDR technology to its fullest potential, several challenges remain, and this chapter has focused on a few of them pertaining to their impact the overall HDR QoE. With regards to HDR processing, tone mapping is often required for HDR viewing on LDR displays, compression, and in many other scenarios where backward compatibility is desired. The aim of this chapter was to throw light on the impact of tone mapping on visual experience.

Specifically, its impact on perceptual quality, visual attention, and naturalness have been disscussed. It is worth highlighting that these play an important role in the QoE in HDR viewing. I've reiterate that HDR viewing experience is more immersive than traditional content due to that fact that HDR attempts to reproduce real-world scene information without undue saturation of visual information. In other words, with HDR we directly deal with physical luminance-related information and this makes the HDR experience more wholesome and enjoyable.

From the objective viewpoint, measuring QoE of HDR remains a challenge primarily due to a larger number of factors involved as compared to traditional video quality. In particular, unlike QoE judgment of traditional visual content, the impact of factors such as naturalness and visual attention modification can be more profound in HDR. Therefore, single measures such as signal fidelity alone cannot be expected to be a reasonable substitute for the overall QoE. On the operational front, HDR poses difficulties because the information is stored in a luminance-related formats, unlike perceptually scaled pixel values in LDR signals. Finally, native HDR visualization is not possible, even with the current HDR display technologies and there is saturation of signal contrast (this is of course due to inherent hardware limitations such as the upper limit on power consumption, heating etc). Addressing some of the mentioned issues will ultimately be the key to large scale practical deployment of HDR and further interesting applications.

Chapter 3 Impact of Tone-mapping Operators and Viewing Devices on Visual Quality of Experience of Colour and Grayscale HDR Images

3.1 Introduction

With many TMOs proposed in recent years, it is unclear which TMO faithfully preserves the structural information in the original HDR images, and which TMO produces natural-looking realistic LDR images for different displays [3]. In particular, a few TMOs are designed for use with small screen devices (SSDs) such as those of mobile phones and tablets [3] [67], [70].

As SSDs are rapidly becoming the leading platform for multimedia content consumption, there is a need to ensure an optimal QoE when viewing HDR content on typical mobile device displays. This problem is exacerbated by the existence of a large variety of brands and models of mobile devices, with their differing resolutions and sizes. It is also unclear whether existing TMOs can be used directly with SSDs. These issues have recently begun to be addressed, but only a small number of studies have been reported so far [35]. The first evaluation of TMOs on a mobile device was carried out by Urbano *et al.* [67], the authors found that the performance of TMO algorithms on SSDs differed significantly compared to the performance on LDRs. However, the study was based on only one mobile device, making difficult to generalise the findings Melo *et. al.* [70] evaluated, six TMOs on HDR video using three different displays including one mobile device (a Tablet) and found significant differences in the TMOs performance between LDRs and SSDs displays. However, only one SSD was used in the study and it was based on HDR video and not HDR image. Another study aimed at SSDs was conducted by Akyuz *et al* [60]; three HDR images of real scenes were evaluated on 24” and 3”displays. They found that the viewing device did not affect the ranking of the image quality significantly. However, the results cannot be generalized to all mobile devices, since the display size of the SSD used was relatively small. In general, the results from previous studies are inconclusive in a number of aspects. For example, Urbano et al. and Akyuz *et al*. found differences in the displays while Melo et al did not. In addition, in all previous studies, the visual QoE of the end-user was not considered [35].

Consideration of the QoE of the end-user is important in order to capture more fully the end-users expectations and viewing experience [35]. HDR should enhance the viewing experience of the end-user and as a result, it is attracting interest both industry and academia as a means of enhancing the viewing QoE in imaging applications However, it is unclear whether different mobile devices have differing influence on the viewing QoE of HDR images, and if so, to how this compares with LDRs [1].

In addition, there are concerns about the use of grey-scale HDR images because there are no TMOs for such HDR images at present. In this thesis, I hypothesize the HDR processing techniques used for colour HDR images should give improved visual QoE for the grey HDR images because the local perceptual contrast in a wider range of the scene will be preserved [36]. Methodology

In this study, we investigated the impact of viewing devices and TMOs on colour and greyscale images using subjective and objective methods. Subjective methods provide a measure and an insight into user-perceived quality. However, they are time-consuming and expensive and as a result, cannot be used for automated quality monitoring or control. Objective methods are based on theoretical models, often based on some characteristics of the Human Visual System and/or image processing techniques [129] [64]. The two approaches are complementary and should enable us to find out how the viewing experience is affected by different devices (LDR/SSD) and the TMO algorithms. The results of subjective tests often serve as ground truth for benchmarking objective measures of perceived quality [3], [70], [61].

3.1.1 Subjective assessment of the impact of TMOS and viewing devices.

Subjective quality assessments provide a good basis for evaluating the strengths and weaknesses of the TMOs and viewing devices and their impact on the QoE. The most common methods used to measure subjective quality are those recommended by the International Telecommunications Union (ITU-R) [102]-[105], [130]. These methods generally require human participants to rate the image quality, individually, on a specified rating scale. The Mean Opinion Score (MOS) (i.e. the mean of the individual quality scores is taken as the final quality rating [104] [105]. In this study, a five-point quality scale was used to rate the quality of the HDR images based on the ITU-R quality rating, see TABLE 3-1. This scale is suited to naïve observers, i.e. non-experts in HDR image analysis, as it is relatively easy to rate the quality of an image based on an adjective ('Excellent', 'Good', 'Fair', 'Poor' and 'Bad') [104]. In the study, we carried out the subjective visual quality assessments in different environments and under different viewing conditions, including outdoor and indoor and with artificial and natural lights.

Table 3-1: Five-level scale rating table

Rating	Definition	Description
5	Excellent	Perfect Image Quality
4	Good	An image with very good quality
3	Fair	Image with good quality, some loss, but overall image is acceptable
2	Poor	Poor quality, low image distortion, but understanding the details
1	Bad	Bad quality, High image distortion, hard to understand the details

Experimental set-up

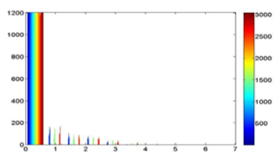
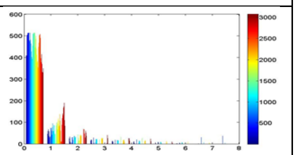
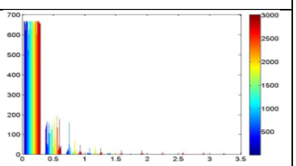
Two experimental setups were designed for the study; one of LDR displays and the other for SSDs. Three colour and three grey HDR images were processed by 10 TMOs, giving a total of 60 colour and 60 greyscale images. The images were then stored in a database accessible from two assessment websites, one website for LDR and one for SSDs. For the LDR assessments, the images were assessed using conventional LDR displays. For SSD assessments, the images were assessed from tablets or mobile phones. The dataset was created using freely available HDR toolbox in MATLAB with, using default settings [52], [131]. All the images used in the study represent natural scenes, and were selected based on their dynamic range, visual quality and content. The original Images and luminance histograms are shown in Figure 3-1. As a final step, gamma correction of 2.2 was applied to compensate for the image luminance of the viewing device [3].

The TMOs used in the study

Ten well-known local and global TMOs were used in the study, Table 2-1 is summaries the features of the different TMO algorithms that were used in the investigation.

Participants

A total of 60 participants were involved in the subjective assessments. The age of the participants was between 20-50 years. They all had normal or corrected vision and no experience of HDR imaging. The assessments had two tests, a Double Stimuli (DS) and a Single Stimuli (SS). In the DS tests the quality of a tone-mapped images are evaluated in relation to the original HDR image TMO. While in the SS evaluation, the original image is not available [132]. At the end of each assessment, the participants submit their individual scores, which are stored in a database for the setup.

Image name	**Original images**	**Luminance histograms ($\log_{10}$)**
Church		
Warwick		
Office		

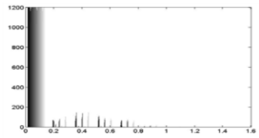
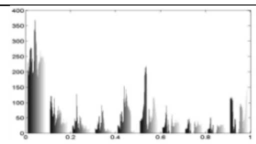
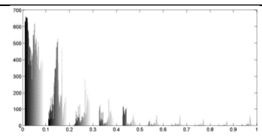
Church_grey		
Warwick_grey		
Office_grey		

Figure 3-1: Original Images and luminance histograms

Ethics

The study protocol was approved by the Research Ethics Committee at Plymouth University.

Devices used in the study

For the SSDs experiments, five different mobile devices were used and involved 30 participants (see Table 3-2). The devices represented popular mobile devices which are used to consume multimedia contents. For the LDR experiment, a display for personal computers were used, In particular, the Philips Brilliance 221P3LPYES display (21.5”, LED-backlit, LCD panel display, 1920×1080 resolution) was used.

Table 3-2: Mobile devices used for the subjective test

Devices	Participants /Device	Features	Resolution / pixels
IPhone 6	9	4.7 “ Retina HD display,	1334×750
IPhone 5S	7	4” Retina	1136×640
Samsung Galaxy Note II	5	5.5“Super AMOLED	1280×720
Samsung Galaxy S4	3	5“HD Super AMOLED	1920×1080
IPad mini 3	6	7.9”, IPS LCD	2048×1536

3.1.2 Objective assessment of the impact of TMOS and viewing devices

A subjective evaluation is a reliable way to assess image quality, but it is expensive and time consuming. It is further complicated by many other factors such as viewing angle/distance, the device, the vision of the subject, and subjects' mood. Thus, there is a need for objective approach to predict image quality [133]. As there is no established model to evaluate the quality of the HDR image at present[3], [72], [54], we used objective quality metrics which have shown promise in other applications in the study. In particular, we have used the following four metrics: Shannon Entropy (SE), Mean Square Error (MSE), the Multi-Exposure Peak Signal-to-Noise Ratio (mPSNR) and High Dynamic Range Visual-difference-predictor-2 (HDR-VDP-2) [134], [135], [136] [64], [108], [114], [115], [132].

Tone-mapping produces images that are different from the original HDR images. In order to fit the resulting image within the dynamic range of the display, tone-mapping algorithms compress, contrast and adjust brightness. Therefore, tone-mapped image may lose some quality when compared to the original HDR images. However, the images would look very similar and the degradation in quality is not very well predicted by most quality metrics [2].

HDR-VDP-2 can predict whether differences between two images are visible to the human observer or not, and can work within the complete range of luminance the human eye can see [2]. mPSNR gives a prediction of the error in the compressed image and is based on the popular PSNR metric [1]. The MSE is the simplest and most widely used metric for image quality [18] [16].

Shannon Entropy

Shannon Entropy [137] provides a statistical measure of the information content of a signal and may be used to characterize the texture of the input image. Low entropy images, such as those containing a lot of black sky, have very little contrast and large runs of pixels with the same values. An image that is perfectly flat will have entropy of zero. Consequently, they can be compressed to a relatively small size. On the other hand, high entropy images such as an image of heavily cratered areas on the moon have a great deal of contrast from one pixel to the and consequently can't be compressed as much as low entropy images [138] [133]. Shannon entropy may be defined as in Equation 1,

$$H(A) = -\sum_{i=1}^{n} p_i \quad log_2 \quad p_i \qquad (1)$$

Where H (A) is the Shannon entropy for the image A, n represents the number of bins (256), and pi is the normalized histogram counts returned from the image histogram for the bin number i. Shannon Entropy is widely used to evaluate grey-scale images and has proved to be efficient, but has not hitherto been used to evaluate HDR image quality for both colour and grey images [36] [134].

Mean Square Error MSE

The MSE is a measure of signal fidelity which enables us to compare two signals by providing a quantitative score that describes the degree of similarity/ fidelity or, conversely, the level of error/ distortion between them [108], [135], [139].The MSE between the images x and y may be obtained using Equation 2:

$$MSE(x, y) = \frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2 \qquad (2)$$

Multi-Exposure Peak-to-Signal Noise Ratio

The mPSNR metric works by converting the original HDR image into multiple LDR images at different exposures and then computing the average of the peak signal-to-noise ratios (PSNR) of each individual exposure. This takes into account both the highlights and the shadows of the image. The resulting mPSNR gives us a prediction of the error in the compressed HDR image, but of course, does not consider the properties of the human visual system [3], [140]. The higher the mPSNR the better the quality of the reproduction is. mPSNR may be computed as in Equation 3:

$$mPSNR = 10\ log_{10}\left(\frac{3\ X\ 255^2}{MSE}\right) \qquad (3)$$

High Dynamic Range Visual-difference-predictor

HDR-VDP-2 is a calibrated visual metric for visibility and quality predictions in all luminance. Although the metric originates from the classical Visual Difference Predictor and its extension HDR-VDP, the visual models are very different from those used in earlier metrics. The HDR-VDP extends Daly's visual difference predictor to predict differences in HDR images [116]. The HDR-VDP-2 was designed to predict visibility rather than quality. In this study, the MATLAB implementation of HDR-VDP-2 was used. But it is also possible to run the metric using an online web service. For the HDR-VDP-2 metric, the parameters were set according to the setup of the subjective evaluations and only the quality value was used [108]

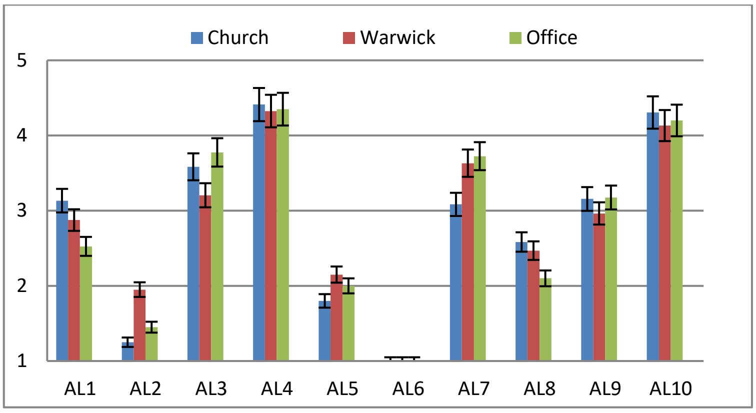
3.2 Results

3.2.1 Results from subjective assessments

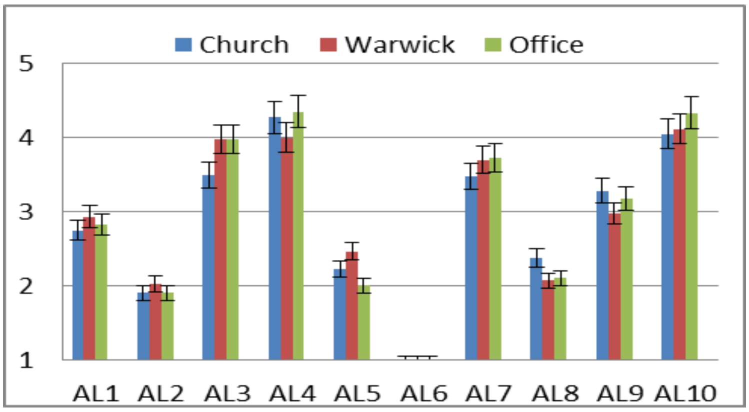
The first step after individual subjective assessments is to determine the overall MOS score, for each image. The raw individual scores were used to obtain the corresponding overall MOS score with 95% Confidence Interval (CI) [78], [101], [132].

Colour HDR images

In this section, the results of subjective rating are described with the aim of understanding characteristics of QoE of the tone mapped coloured HDR images and factors that affect QoE in different devices. The results for the SSD experiments for different TMOs are shown in Figure 3-2 (a) and (b). For the DS tests (see Figure 3-2(a)), the TMOs *Al4* and *AL10* (i.e. iCAM06 and Bilateral Filtering) gave the best MOS scores for all the images. These two tone-mapping operators preserve image details in relation to the reference image. The worst TMO for all the images was *AL6* which had a MOS score of 1 in all cases. For the SS tests (Figure 3-2-b): *AL4* and *AL10* again had the best MOS score. *AL3* and *AL1* achieved a MOS score of between 3.5 and 4 which is good. *AL6* had a MOS of 1 which is the lowest.



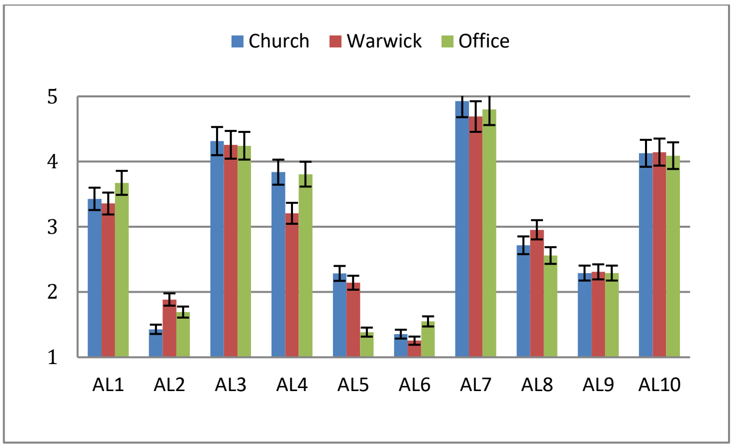
a



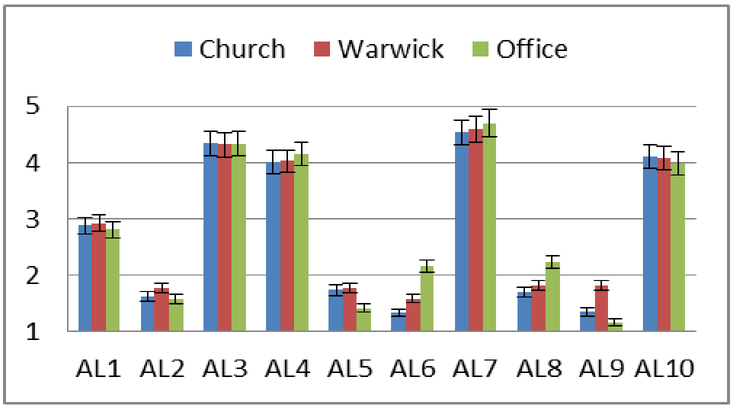
b

Figure 3-2: Impact of TMOs on MOS for different Coloured HDR using SSD

The results for the LDR display experiments are shown in Figure 3-3, (a) and (b). In the DS tests, (Figure 3-3 (a)), AL7 gave the highest MOS score for all images, with a MOS score of about 4.5, followed by AL3 and AL4 with MOS scores of around 4. It is worth noting that AL7 is based on luminance's logarithmic compression, while AL3 and AL4 are based on an efficient way of reducing halo artefacts by compressing the dynamic range of the HDR image which results in a very good HDR image quality [3], [4]. On the other hand, the TMOs AL5 and AL6 gave the worst MOS scores of all the TMOs. The poor MOS results for AL6 are thought to be because after tone-mapping with the AL6, the images may still present halos and this affects the overall quality. In the SS test (Figure 3-3, b), the performance of the TMOs follow a similar pattern to those in the DS tests, but with minor differences for the best and the worst TMOs [61]. In both SSD and LDR tests, *AL6* had the lowest MOS score (MOS score of 1) compared to other TMOs. The SSDs used in the study have different display features (including different screen sizes and screen resolutions, see TABLE 3-2) and these are thought to impact on the perceived viewing quality.

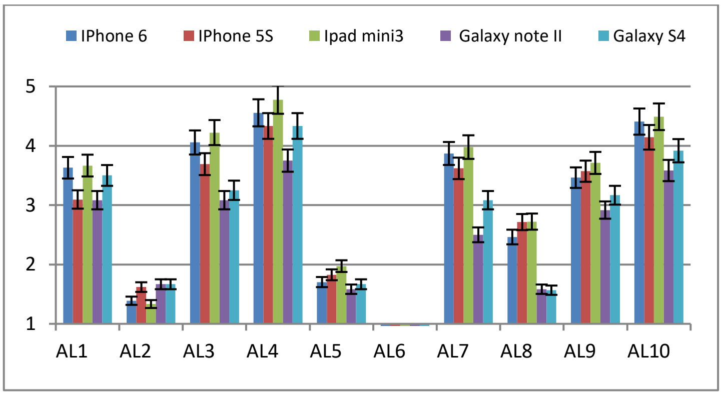


a

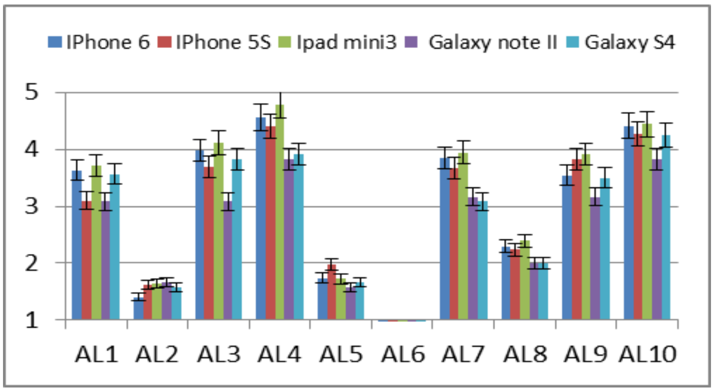


b

Figure 3-3: Impact of TMOs on MOS for different Coloured HDR using LDR, (a) DS test, (b) SS test.



a



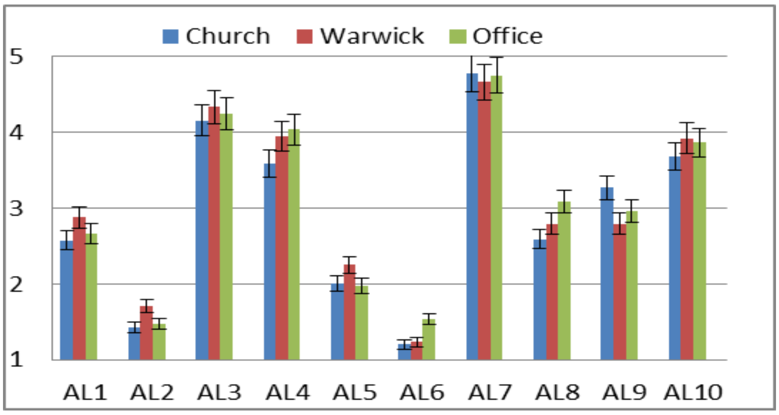
b

Figure 3-4: Impact of SSDs on TMO quality for coloured HDR, (a) DS test, (b) SS test.

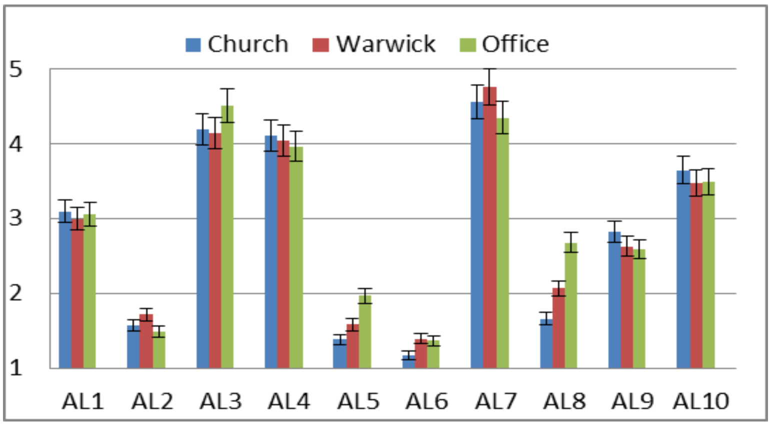
Figure 3-4 (a) and (b) shows the results of the impact of the SSDs in uncontrolled viewing conditions in both SS and DS tests. In both tests, the results suggest that the size and resolution of the screen have the most impact on the MOS values achieved. The best results were achieved with the iPad mini 3 followed by iPhone 6 and then iPhone 5S. Samsung Galaxy Note gave the lowest MOS score. In conclusion, we found that QoE is affected mostly by the resolution of the SSDs. However, we found that there is no significant difference in the performance of SDDs for HDR images for both SS and DS tests.

Greyscale HDR images

In this section, the results of the subjective rating of the tone mapped greyscale HDR images are presented to provide an understanding of the impact of viewing displays and TMOs on perceived quality. The results for the LDR display experiments are illustrated in Figure 3-5 (a) and (b) for three tone-mapped images. From the figure, it can be seen that the best performance was achieved with the two TMOs *AL7* and *AL3* with MOS scores of around 4. Figure 3-6 (a) and (b) show the impact of TMOs on MOS of different greyscale HDR images using SSDs for DS and SS tests respectively. Examination of the results shows that *AL4* and *AL10* had the best performance, with a very good MOS score for all the images, while *AL6* was the worst TMO, with the lowest MOS score.

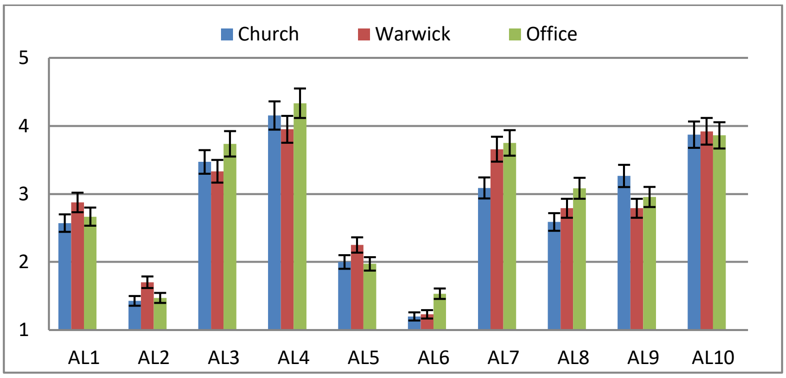


a

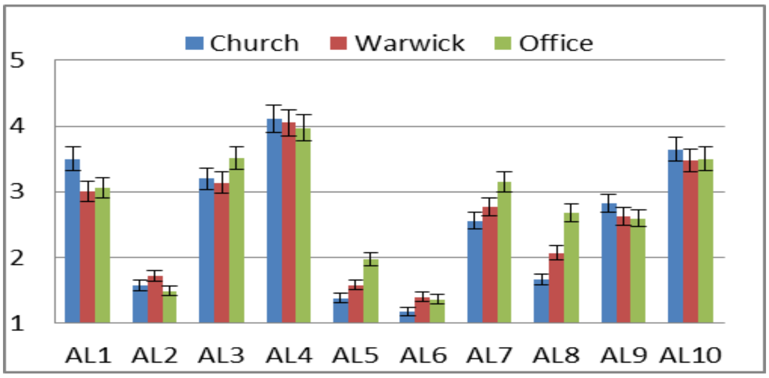


b

Figure 3-5: Impact of TMOs on MOS for different Greyscale HDR, (a) DS test, (b) SS test.

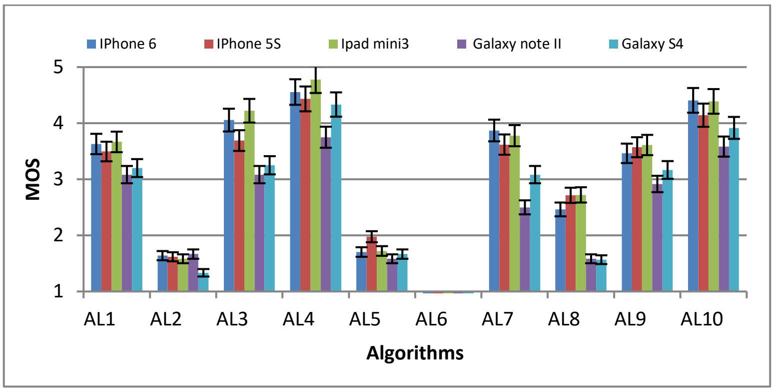


a

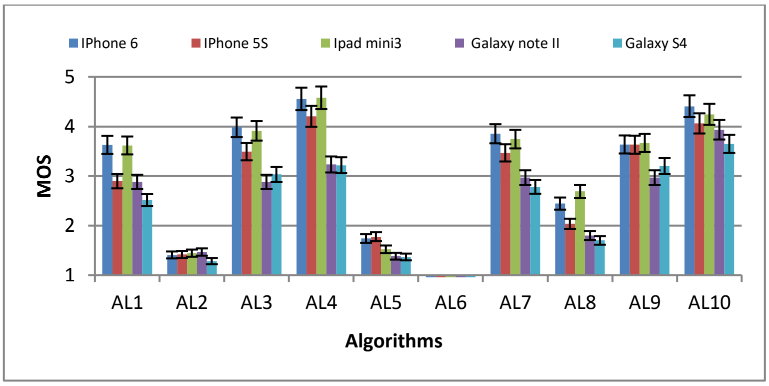


b

Figure 3-6: Impact of TMOs on MOS for different Grey-scale HDR using SSD, (a) DS test, (b) SS test.



a



b

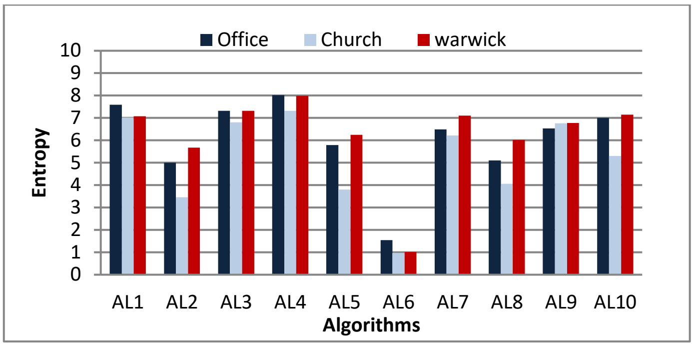
Figure 3-7: Impact of SSDs on TMO quality for Greyscale HDR, (a) DS test, (b) SS test.

Figure 3-7 (a) and (b) shows the results of subjective tests for SSDs for grey images using DS and SS tests. The results show that the best result was achieved by using an iPad mini 3 compared to other devices. This is followed by iPhone 6 and the iPhone 5S. In both the SS and DS tests, the results suggest that the SSDs resolution has an impact on the perceived viewing quality.

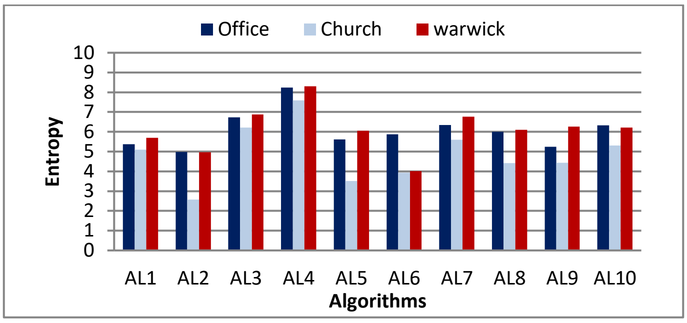
3.2.2 Results from objective assessments

Shannon Entropy: The entropy values for the original images (i.e. Office, Church and Warwick) are: 6.2457, 4.5064, and 6.5698 respectively. Figure 3-9 (a) and (b) shows the results of Entropy for colour and greyscale images, respectively the results show that *AL4* had the highest MOS score, with entropies of 8.0117, 7.3216 and 7.9902 for office, church, and Warwick, respectively. *AL3* was second in performance with the entropies of 7.3225, 6.8097 and 7.3234 for office, church, and Warwick respectively. *AL3* (Drago) and *AL4* (modified iCAM) had the best performance because they give good contrast images while recovering the details of the saturated regions. Therefore, the outputs of these algorithms have a wide histogram and less saturated pixels. Both algorithms use Entropy to define the details in the input images [37], [55], [133].

The worst Entropy result was for *AL6* and *AL2* for Church image. This is due to the fact that in the Church image the only source of light was natural light coming in from the windows, while the rest of the church was relatively dark. It spans a wide dynamic range and has many detailed features that will result in a very wide histogram as we can see from Figure 3-8. As Shannon Entropy is a count of histogram returned from the image, the Entropy for Church is less than for the other coloured and grey images.



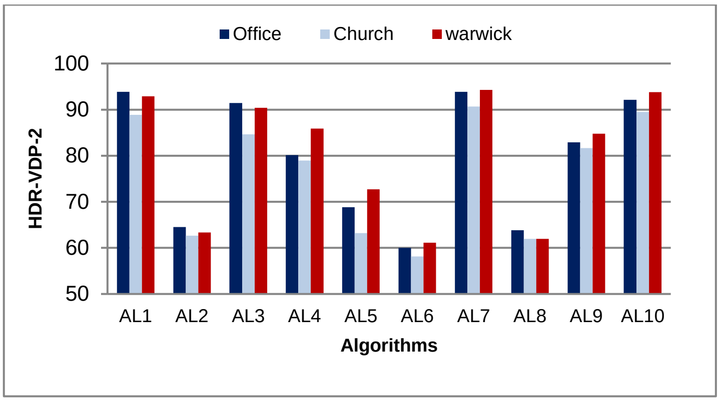
a



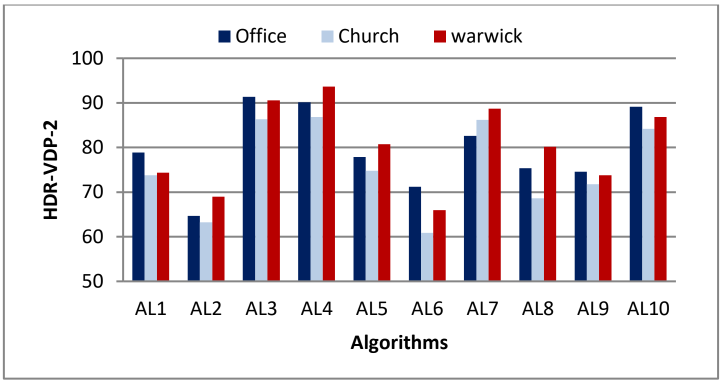
b

Figure 3-8: Entropy results (a) Colour, (b) Grey

High Dynamic Range Visual-difference-predictor HDR-VDP-2: The results for HDR-VDP-2 are depicted in Figure 3-9 (a) and (b). They show that *AL7, AL1, and AL10* have the highest scores while *AL6, AL8 and AL2* have the lowest score. It is noteworthy that the high - performing operators follow HVS functionality [37]. The HDR-VDP-2 is a map of probability for perceiving visible changes between an HDR image and the corresponding LDR image, i.e., the position of each pixel has a corresponding probability that any visual change can be detected [16] [18]. On the other hand, comparison of Figure 3-9 (a) and (b) show that there is a significant difference between the results for *AL1* for grey and colour images. Ashikhmin operator *AL1* computes a measure of the surround luminance for each pixel. This measure is then used for the definition of the tone mapping operator [116]. To conclude, an algorithm that produce better image quality if its HDR-VDP-2 maps contain more pixels with a lower probability of detecting a visible change [141].



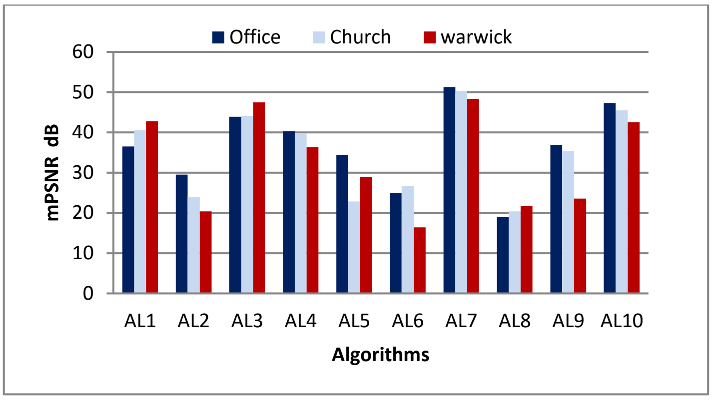
a



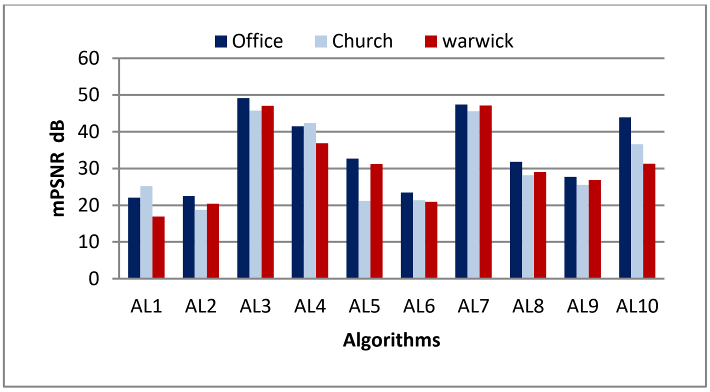
b

Figure 3-9: HDR-VDP-2 results (a) Colour, (b) Grey

Multi-Exposure Peak-to-Signal Noise Ratio mPSNR: The results of the Multi-Exposure Peak Signal-to-Noise Ratio (mPSNR) i shown in Figure 3-10 (a) and (b). For colour images, Figure 3-10 (a), *AL7* gave the best results. The two images, Office and Church, had the best results for mPSNR (>50 dB), while, the image, Warwick, was second with a mPSNR of 48 dB. *AL10* had mPSNR values of 47, 45 and 42 dB for the three images Office, Church and Warwick, respectively. The worst TMO was *AL8* with mPSNR of less than 21 dB for all the images, *AL6* was also poor for the three images, with mPSNR values of less than 26 dB. In Figure 3-10 (b), it is seen that *AL3* gave the best mPSNR values (close to 50 dB) for the three images.



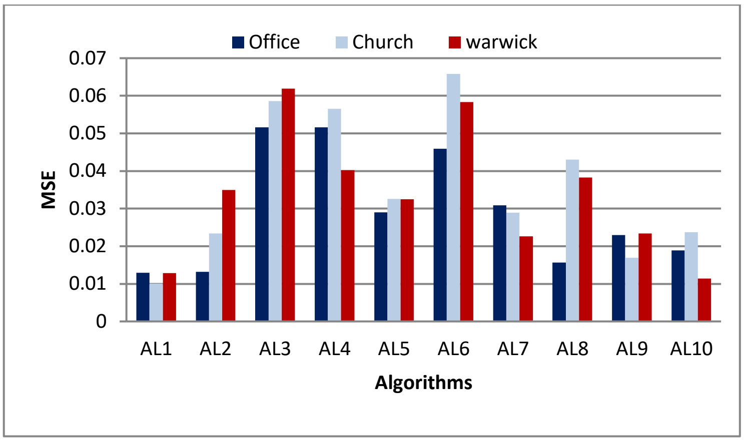
a



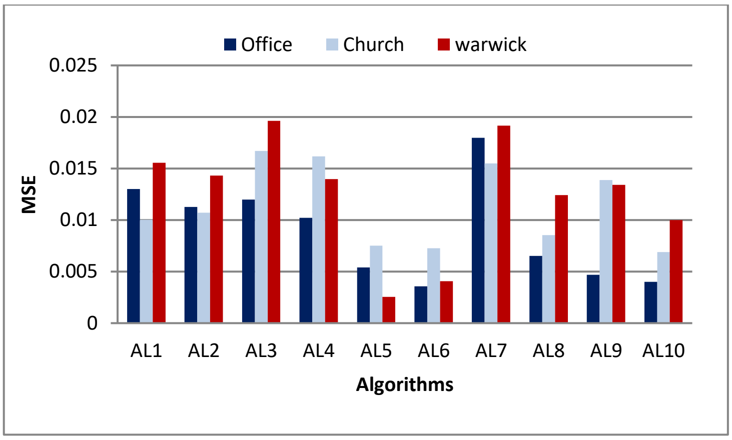
b

Figure 3-10: mPSNR result, (a) Colour, (b) Grey

Mean Square Error MSE: Figure 3-11 show MSE results for (a) Colour, (b) Grey, in (a) we can see that *AL1* performed best with an MSE of less than 0.02, followed by *AL9* with an MSE of around 0.02. The worst performance was for AL3, AL4, and AL6. For grey images, Figure 3-11(b), the best performing TMOs were *AL6* and *AL5*, which had MSE values of around 0.005. The worst performance came from *AL3, AL4,* and *AL7*. MSE and mPSNR simply quantify the error signal and do not model the human visual system. They have low computational complexities compared to image similarity measures which model the HVS [135].



a



b

Figure 3-11: MSE results, (a) Colour, (b) Grey

3.2.3 Correlation between subjective and objective assessments of HDR image quality

Three performance indices were used in the study to assess the results of the subjective and objective quality assessments - the Pearson linear Correlation (PLC), Spearman Rank Order Correlation (SRC) and Kendall rank correlation (KRC). PLC is a measure of the degree of association between two variables, whilst SRC measures the prediction monotonicity and KRC evaluates the similarity between two variables. The performance indices may be used to determine the best method for viewing HDR images using SSD from the user's perspective [61].

Subjective tests: Table 3-3 summarises the correlations between the perceived quality (MOS values) for colour and grey images in the DS tests with those in the SS tests across all the TMOs. The first row in the table gives the correlation coefficients between the perceived quality in the DS tests and the perceived quality in the SS tests for colour HDR images across all the TMOs. In this particular experiment, the high correlation coefficients for PLC and SRC suggest that the perceived quality for DS and SS tests are closely related, implying that it may not matter whether we use DS or SS tests to assess the quality. Similar results were obtained between the DS and SS tests (third row) for grey images. The second row gives the correlation between the perceived quality for colour HDR images in the DS tests and those for greyscale images in the SS tests. The high correlation here and in the fourth row (correlation between the perceived quality of colour and grey images) suggests that the same TMOs may be used for both colour and grey images. However, in general, participants preferred colour HDR images to grey images.

Table 3-3: Correlation between the subjective experiments

Group	PLC	SRC	KRC
DS Colour / SS colour	**0.9209**	**0.9152**	**0.7778**
DS Colour / SS Grey	0.7293	0.7697	0.6000
DS Grey / SS Grey	**0.8910**	**0.8303**	**0.6444**
SS Colour / SS Grey	0.7113	0.7939	0.6444

Table 3-4 summarises the correlation coefficients and hence the relationships between subjective and objective quality assessments for different objective quality metrics. They show that for colour HDR images, HDR-VDP-2 gives the best objective quality measures (in both DS and SS tests). For greyscale images, the entropy is the best. Overall, HDR-VDP-2 and entropy are the best objective metrics for predicting perceived quality and MSE the worst. Entropy performed better for grey images than for colour images. This is because a greyscale image is a simple image in which the colours are only shades of grey. A `grey' color is one in which the red, green and blue components all have equal intensity in the RGB spaces and so it is only necessary to specify a single intensity value for each pixel as opposed to the three intensities needed to specify each pixel in a full-color image [36] [134]. In both colour and grey images the MSE, which is a full reference metric, was the worst metric. This is because the MSE does not consider the characteristics of HVS and, so it may not always be significantly correlated with subjective visual quality [135].

Table 3-4: Correlation between MOS and objective quality Metrics

DS colour	**PLC**	**SRC**	**KRC**
mPSNR	0.7552	0.6848	0.4666
HDR-VDP-2	**0.9398**	**0.8545**	**0.6889**
Entropy	0.8548	0.8061	0.6444
MSE	0.3112	0.2193	0.1794
SS colour	**PLC**	**SORC**	**KRC**
mPSNR	0.7665	0.7024	0.6444
HDR-VDP-2	**0.9051**	**0.7455**	**0.5111**
Entropy	0.8236	0.6848	0.4667
MSE	0.3716	0.2044	0.1392
DS Grey	**PLC**	**SRC**	**KRC**
mPSNR	0.7913	0.5879	0.3333
HDR-VDP-2	0.8043	0.7376	0.5156
Entropy	**0.8842**	**0.7533**	**0.5511**
MSE	0.4147	0.3863	0.3212
SS Grey	**PLC**	**SRC**	**KRC**
mPSNR	0.509	0.5394	0.3778
HDR-VDP-2	0.682	0.7333	0.6001
Entropy	**0.791**	**0.8182**	**0.6444**
MSE	0.391	0.4911	0.2252

3.3 Discussion

The aim of this study is to investigate the impact of viewing devices and TMO algorithms on the visual quality of experience for both colour and greyscale images. We found differences in the visual quality between LDRs and SSDs in the tests. For

SSDs, the best TMO was *AL4* (iCAM06) and for LDR it was *AL7* (Photographic Reproduction). Both iCAM06 and Photographic Reproduction preserve the edges, which improves the grey level distribution of the generated LDR image during tone mapping which helps to provide better QoE for the end-user by avoiding contouring and retaining more details.

For the different TMOs, we found that subjective results for SSDs were better than those for LDR. Moreover, there was no significant difference in the subjective quality of using mobile devices to view HDR images in both the DS and SS tests. Similar results were obtained from grey HDR images even though colour images may lose important information when transferred to a greyscale image [21]. We found that the impact of colour has less impact in HDR images than in conventional digital image technology. HDR imaging capture illumination in a higher range, which provides more detail and edge information and better viewing experience [1-4] [6-10] [20].

In the SSD experiments, we found that the iPad MINI 3 and iPhone 6 for both coloured and grey images gave the best-perceived quality. We found that better subjective results are associated with larger SSD resolution. Moreover, the results indicate that SSD size and resolution have an influence on the tone-mapped image reproduction for both coloured and grey HDR images Mobile devices are now widely used as a platform to consume multimedia information. The rapid growth in the number of mobile devices in use will bring about a demand to optimize the end user QoE when viewing HDR content.

3.4 Summary

We have evaluated, subjectively and objectively, the most widely used TMOs in different displays and resolutions to provide an understanding of the impact of viewing devices and TMOs on the visual quality of experience for both colour and greyscale HDR images. Our results suggest that the user’s QoE of tone-mapped images were significantly different on LDR compared to SSDs. SSDs have an influence on the

TMOs performance compared to LDR's. In general, better subjective results relate to the size and resolution of SSD. We found that iCAM06 performed the best TMO for SSD and Photographic Reproduction for LDR it was performed the best TMO for both colour and greyscale HDR images. Also, we found that there was no significant difference between the subjective score for colour and grey images in SSD, while there is a difference between LDR and SSD. The device and the TMOs appear to affect the quality of both colour and grey equally. For the objective metrics, Shannon Entropy was found to be a good measure of the QoE for both colour and grey HDR images, suggesting that it may find use in automated quality control assessment schemes for HDR.

Chapter 4 Investigation of relationships between changes in EEG features and subjective quality of HDR images

4.1 Introduction

QoE is an important issue in various image and video applications. It is necessary to understand how humans perceive quality from visual stimuli as this can be potentially exploited for developing and optimizing images and video processing algorithms [15]. Recently, image consumption using mobile devices has become increasingly popular because of the availability of smartphones capable of producing and consuming HDR images and advances in high-speed wireless communication networks. One of the most critical issues in mobile HDR image delivery services is how to maximize the QoE of the users for the delivered contents [70], [142]. An open research question is how HDR images with different contents perform on mobile phones. Traditionally, evaluation of the perceived quality of multimedia content is done using subjective opinion tests, such as MOS. However, it is difficult for the user to link the experienced quality to the quality scale. Moreover, MOS does not give an insight into how the user really feels, at the physiological level, in response to dislikes or satisfaction with the perceived quality[10], [11], [143].

To address this issue, measures which can be taken directly (implicitly) from the participant have attracted interest. An electroencephalogram is a promising approach which may be used to assess quality related processes implicitly[144]. At present, there is no standard for using electrophysiology to assess QoE, but contributions are being made to the ITU-T on the use of physiological measures for QoE (e.g. ITU-T Contribution COM 12-(039, 112, 103, and 202) [104], [105]. However, implicit QoE approaches are still in the early stages and further research is necessary to better understand the nature of the recorded neural signals and their associations with user-perceived quality from QoE perspectives.

We propose a novel electrophysiology-based QoE assessment approach for HDR image quality which may be used to predict perceived image quality. Previous studies [13], [10], [12], [39], [2] have demonstrated that physiological measurements provide valuable insight into QoE of advanced media technologies. In our study, the correlation between the mean power in the delta and beta bands is used as a measure of the coupling between the activities in these bands. This is linked with negative behavioural characteristics (e.g. anxiety, frustration, dissatisfaction). Our study is based upon clinical findings [43], [44], [145], [146], [147], which suggest that increased EEG delta-beta coupling promotes behavioral inhibition states. Thus, increases in the degree of coupling are associated with decreases in HDR quality. This has not hitherto been used in electrophysiology-based QoE assessment for HDR image quality. This approach may provide an insight into human preferences and perceptions about a service or product and hence user-perceived quality. The specific objectives of the study are:

- To investigate changes in brain activities during HDR image quality assessment.
- To understand the changes in the EEG which are related to HDR image quality perception in terms of QoE?
- To investigate the relationships between the coupling between delta and beta activities and the MOS.

We have used HDR imaging in the study as it has emerged as one of the most promising recent developments in multimedia technology and which has wide applications. 20 HDR images which have been processed by four different TMOs (Tone-Mapped Operators) were viewed by 28 subjects on small screen devices (SSDs). The MOS scores were obtained and the EEG data recorded during the test. The relationships between MOS and EEG features were then investigated. Results show that changes in the gamma and beta bands correlated negatively with MOS, whereas positive correlations were observed in the alpha band. The beta band had the most significant association with ($P > 0.001$) MOS. Analysis of the results showed that EEG-based measures provided additional information in understanding human perception of the contents.

4.2 Related work

4.2.1 Electroencephalography in HDR

There has not been much research regarding the evaluation of HDR image quality using EEG measurements. Often, the EEG is used in brain-computer interface (BCI) applications, where it assists users in image classification tasks [14]. Hayashi et al [14]used the EEG to evaluate the quality of high-resolution images and found that images with good quality produced a higher amount of alpha activity than images with poor quality. Kroupi et al. [2] analyzed the degradation of 2D and 3D videos using sequences from a music festival. They found that the EEG shows a high frontal asymmetry in the alpha power band, reflecting emotional affect towards the two different quality levels. Moon et al. [12], [16] used four different HDR and LDR (low dynamic range) video contents. The power in the bands was extracted from the EEG data as features and used for classification. This gave an accuracy of almost 70% if only EEG features were used and almost 80% if other peripheral measures were used for classification as well. Moreover, gamma band gave the most discriminative results between conditions. The above studies focused only on one frequency band (e.g. alpha or gamma) and did not investigate in detail the association between the bands or the relationships with the QoE. Furthermore, previous studies all used sophisticated, hospital-grade, EEG devices in the lab environment which are not widely accessible for QoE assessment purposes. Few research studies have explored the potential of portable EEG devices for multimedia quality assessment.

Moldovan et al. [13] used features provided by the Emotiv EPOC System to infer the level of frustration from the human observer caused by the quality of audio-visual excerpts. This level was based on a metric predefined by the headset manufacturer for different levels of video quality. The level of quality was controlled by changing the bit rate, frame rate as well as the resolution of the presented video clips. Perez et al. [148] used the Neuro-Sky Mind-Wave headset to measure brain activity and used the recorded data to classify the trials into high and low-quality pictures. All the above studies were focused on voice/video quality, but not on HDR images.

4.2.2 Delta-beta coupling

Delta-beta coupling (positive correlation between power in the fast beta and slow delta frequency bands) has been related to affective processing [43], [44], [145], [146], [147]. For instance, differences in delta-beta coupling have been observed between subjects in a psychological stress condition and controls and have been linked with negative behavioural characteristics (anxiety, frustration, dissatisfaction). In Gray's theory [44], the authors suggested that delta-beta coupling appear only in a frustrating situation, that is, it should be state-dependent. Another important point is that for anxiety generation, there must be concurrent and equivalent activation of fear and approach systems. Laghari et.al [43] computed the EEG feature based on the coupling between delta and beta EEG frequency bands. The result indicates an increase in delta and beta coupling with a decrease in the speech quality levels. Additionally, neural correlates of subjective affective scores (arousal and valence) were also computed and shown to be inversely proportional with EEG feature. In Knyazev et.al [145], it is shown that the correlation between mid-frontal delta and beta spectral power increased in healthy male subjects with an increase in anxiety and behavioural inhibition. It has also been found that there is a higher positive correlation between delta and beta powers in subjects with a higher baseline level of salivary cortisol (the steroid hormone directly associated with anxiety. A hypothesis is that coupling reflects higher cortical arousal in frustrating situations [146], [147]. It has also been found that coupling is very sensitive to external influences since it allowed detection between good and bad performance conditions [44].

4.3 Data collection

In this study, explicit subjective tests and implicit tests using the EEG were conducted. The study involved several participants viewing and rating the quality of HDR images with different TMOs while their EEG data were recorded at the same time.

4.3.1 Participants

Twenty-eight subjects including 13 female and 15 male (Mean= 30.6, SD= 3.890, the age range of 25- 45 years old), all right-handed participated in the test. All subjects had a normal or corrected vision and are non-experts in HDR. However, they all have a clear understanding of the test and are all postgraduate students. Before each experiment, a training session was given to allow participants to familiarize themselves with the procedure. The images used in the training session were different from the test stimuli. Figure 4-1 shows the participant preparation before the experiment.

4.3.2 Ethics

The study protocol was approved by the Research Ethics Committee at Plymouth University.

4.3.3 Tests stimuli

Five HDR images were selected for the study, based on their visual content, quality, and the dynamic range. The five images were each processed by four TMOs, giving 20 HDR images. The best four TMO from our previous study were used [35], AL1: Adaptive Logarithmic; this is a fast algorithm suitable for interactive applications which automatically produces realistically looking images for a wide variation of scenes exhibiting a high dynamic range of luminance. AL2: iCAM06; this is based on the physiology of the human's eye photoreceptors. The output of the operator is a combination of a locally adapted value around each pixel of the image and a globally adapted value based on the image averages. *AL3: Photographic Reproduction*; this is based upon dodging-and-burning in traditional photography. It automatically applies various scales for luminance mapping to the prorated regions of highlights and shadows. *AL4: Bilateral Filtering;* this is fast bilateral filtering for the display of HDR images conserving local details in the image. The images used for the validation was computed using a MATLAB® HDR toolbox. The default settings of the operators' performance were used.

4.3.4 EEG signal acquisition

A portable EEG device (HeadCoach™, Alpha-Active Ltd, Devon, UK) [149] was used to record scalp electrical activity, with a sampling frequency 128 Hz, band-pass filter, 0.5-60 Hz, from two active (positive inputs) electrodes, placed at Fp1 and Fp2 according to the 10-20 EEG system [121]. Before the electrode placement, the skin was prepared with an abrasive skin preparation gel (Nuprep™, Weaver and Company, Aurora, USA) and then cleaned with an alcohol-free wipe. The spectrum of the recorded is computed and the time and frequency domain data were stored in CSV format for subsequent analysis.

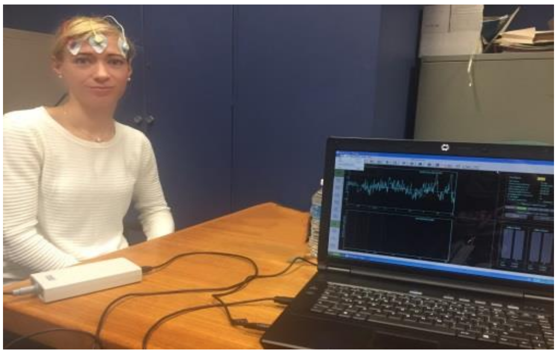


Figure 4-1: A participant preparation before the experiment

4.3.5 Test setup

The set-up for the test is illustrated in Figure 4-2. An iPhone 6 device running on the IOS operating system was used to display the HDR images. This has a 4.7-inch Retina HD display with a resolution of 1334×750. An Intel Core™ i7 PC running Microsoft Windows 7 Enterprise operating system was used to process the EEG data. The iPhone and the EEG recording PC were time synchronized to facilitate the data analysis.

4.3.6 Test methodology

The experiment consisted of two sessions. During each session, 10 stimuli were displayed on the device. Half an hour break was given between the two sessions to prevent lack of attention and fatigue and to ensure comfort. Each session lasted approximately half an hour, excluding the training and the setup of the EEG devices. Each trial consisted of a 30-second baseline phase, an HDR stimulus period and a rating phase as shown in Figure 4-3. During the baseline period, subjects were instructed to remain calm and to focus on a 2D white cross on a grey background presented on the screen in front of them. The EEG signals recorded during the baseline period were used to remove stimulus-unrelated variations of the signals acquired during the stimulus period. Once the baseline period was over, an HDR image stimulus was presented for 30 seconds. At the end of this, subjects were asked to provide their ratings for the HDR image stimulus within 60 seconds. After the participant has submitted the rating, the next stimulus appears on the SSD, with the order of sessions and trials randomised. The test sequences and quality ratings were displayed on a website. Subjects were asked to evaluate the HDR stimuli (see Figure 4-2). We chose a discrete five-level rating scale (ITU-R quality ratings [104]), which is suitable for naïve observers (non-experts in image processing) and is relatively easy for them to use it to quantify quality ('5=Excellent' and '1=Bad') [6]. Figure 4-3 illustrates an example of a test trial, including baseline, stimuli, and rating period.

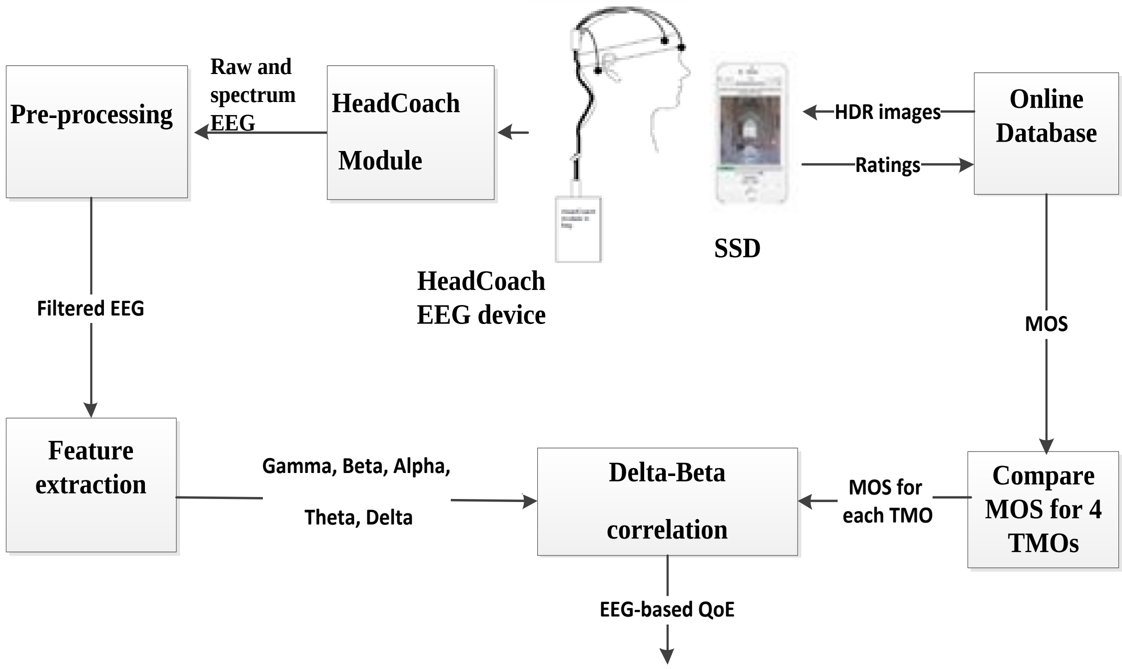


Figure 4-2: The test-bed for HDR image quality assessment

4.3.7 Pre-processing

For EEG analysis, the MATLAB toolbox EEGLAB was used. The recorded EEG signals were filtered using an IIR filter to extract the frequency bands of interest between 0.5-60Hz. Thirty-three seconds of data were recorded for each subject, but only the last 30 seconds of all signals were used in our analysis, considering that stabilization and adaptation of the HDR contents may take some time.

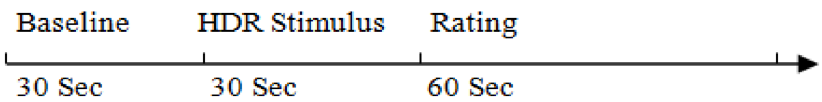


Figure 4-3: Trial timeline

4.3.8 Feature extraction

The baseline power was subtracted from the trial power, yielding the change in power relative to the pre-stimulus period. These changes in power were averaged over the frequency bands, namely delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz) and gamma (30-60 Hz) frequency bands, for each channel. Delta activity is present during sleep and continuous attention; theta activity occurs during light sleep and provides an indicator of decreased alertness and for encoding new information. Activity in the alpha band is related to alertness and good quality images and is a function of age.

Beta activity is related to cognitive thinking and visual attention and is significantly increased in a 3D environment. Finally, gamma band is related to visual information processing, brain activity and good quality image [9].

4.4 Results

4.4.1 Subjective rating analysis

In this section, the results of subjective rating are described with the aim of providing an understanding of the characteristics of QoE of the tone mapped HDR images and factors that affect QoE. The first step was to detect and remove outliers in the subject MOS results so that they do not influence the results. Outlier detection procedure was applied to the results obtained from the 28 subjects and performed according to the guidelines described in Section 2.3.1 of Annex 2 of ITU-R BT.500-13 [104]. MOS representing the average subjective quality ratings across all participants are usually represented on nominal scales and associated 95% Confidence Interval (CI) were presented for the five quality level algorithms as recommended in ITU-R BT.500-13. Figure 4-4 is the average MOS for *AL1, AL2, AL3* and *AL4* respectively; Bilateral Filtering *AL4* had the best performance from the observers' point of view.

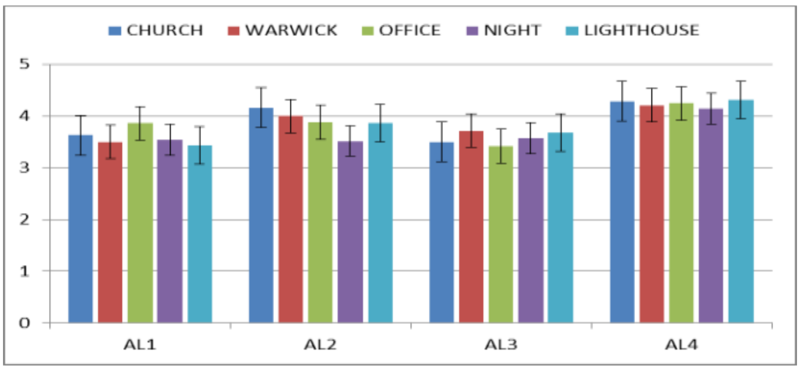
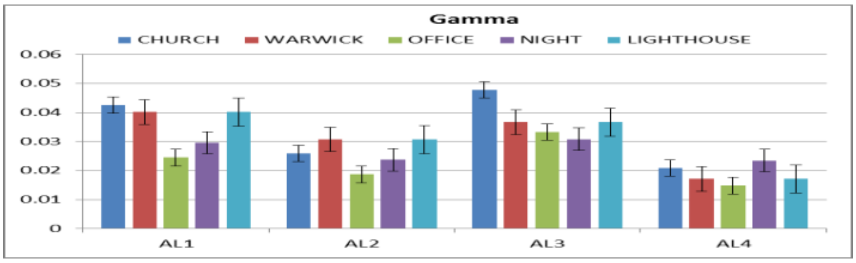


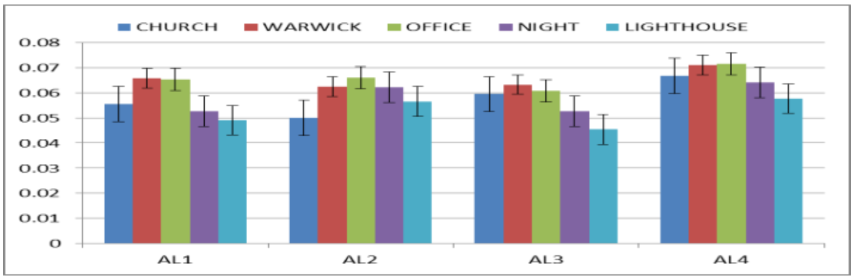
Figure 4-4: MOS and CIs for experienced TMOs

4.4.2 EEG signal analysis

It is known that high gamma power corresponds to high brain activity and that the brain is highly activated when the perceived quality is low. This indicates that perception of



a



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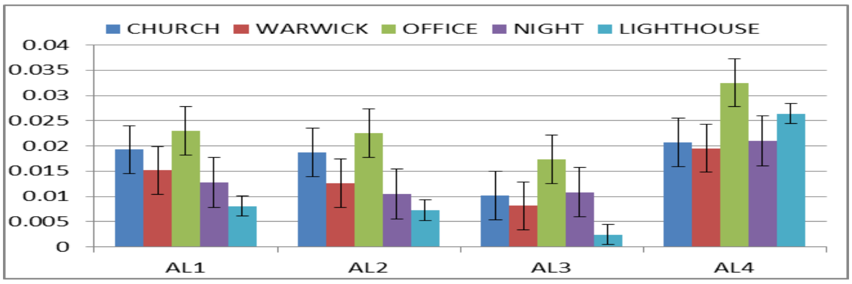

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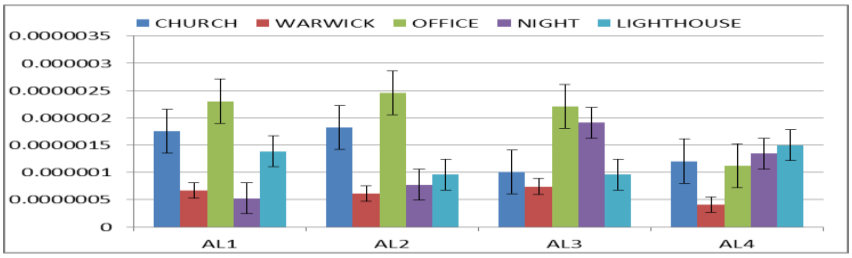

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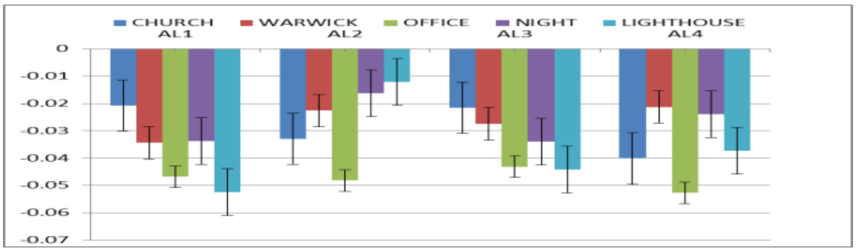


e

Figure 4-5: Mean power for (a) Delta (b) Theta (c) Alpha (d) Beta and (e) Gamma

low quality is related to negative emotions [2], [12], [16], [43], [148]. It also implies that higher gamma means lower quality for the HDR image (Figure 4-5.a). AL4 gave the lowest results, which indicates that it has the highest quality. In accordance with [150]-[153], we also found a significantly higher beta for positive emotional tasks (high perceived HDR quality in our case) compared to other frequency bands results. Therefore, cognitive and emotional processes seem to take place during the quality perception of HDR images. From the beta results, Figure 4-5.b, there is no large variance in the mean power level. This suggests that the brain reacted cognitively and emotionally with the HDR images in the same way. Furthermore, high alpha power indicates brain activation when overall perceived quality is high, whereas alpha power in the brain is deactivation when overall perceived quality is low [123], [15], [39], [2], [148]. Figure 4-5.c, *AL4* gave the highest Alpha result, i.e. best-perceived quality. In the theta frequency band, Figure 4-5.d, EEG power is negatively related to cognitive performance and brain maturity, theta synchronization is positively correlated with the ability to encode new information [16]. From the results, we can see that theta mean power amplitude is very low (~10^{-5}) compared with all other frequencies, which is an indicator of increasing alertness [16].

4.4.3 Correlation and analysis of variance

To estimate the correlation between changes in the EEG and subjective scores, the mean of all power in the frequency band across subjects was calculated. The Pearson linear Correlation Coefficient was calculated between the mean power values and the MOS for subjective ratings, per frequency bands (see TABLE 4-1). From TABLE 4-1 we can see that the highest correlation is between MOS and gamma frequency band [70], [148], but this is negatively correlated; Thus, higher gamma means lower quality for the HDR image. The AL4 TMO gave the highest correlation.

The results also show that Alpha is positively correlated with MOS and that AL4 gave the highest correlation. The correlation values for the beta band, however, were not high but they followed the hypothesized inverse relationship trend. This is probably because the subject’s judgement may not always follow the objective neurophysiological facts. Additionally, it is likely due to the neutrality of the content utilized for the HDR stimuli, which may not have evoked strong enough emotional characteristics [2], [12], [13]. Theta and Delta correlate positively, but the correlation is weak.

Table 4-1: Pearson correlation between MOS and the frequency oscillations for each algorithm (quality)

	AL1	AL2	AL3	AL4
Gamma	-0.6605	-0.8132	-0.5660	**-0.8747**
Beta	-0.6005	-0.6492	-0.6012	**-0.6820**
Alpha	0.5320	0.7523	0.5004	**0.7830**
Theta	0.2648	0.2592	**0.3336**	-0.1039
Delta	0.0637	**0.2211**	0.0477	0.0814

The Spearman correlations were estimated between the mean power values for each frequency band and the subjective ratings, for all image contents (see TABLE 4-2). We found significantly higher beta in *Night* and *Lighthouse* compared to *Church, Warwick* and *office* for positive emotional tasks (preferred content in our case). Hence, cognitive and emotional processes seem to take place during the quality perception of the HDR image. An increase in alpha and theta level is the result of a reduction in quality. This increase may be due to an increased the level of anxiety, fatigue and drowsiness. We found significantly lower alpha and theta in *Night* and *Lighthouse* compared to *Church, Warwick* and *Office*. This finding implies that subjects in this study rated perceived quality by taking into account how pleasant or annoying the content was. Moreover, high gamma power corresponds to high brain activity and suggesting that the brain is highly activated when perceived quality is low [89], [127]

Table 4-2: Pearson correlation between MOS and the frequency oscillations for each content.

	Church	Warwick	Office	Night	Lighthouse
Gamma	-0.7301	-0.7971	-0.808	-0.362	-0.4675
Beta	-0.5632	-0.4345	-0.443	-0.739	-0.8091
Alpha	0.5857	0.4155	0.6622	0.1765	0.1144
Theta	0.4328	0.4774	0.5769	0.1976	0.1649
Delta	0.1264	0.1109	0.0846	0.0109	0.0116

We found significantly lower gamma in *Night* and *Lighthouse* compared to *Church, Warwick* and *office*; this indicates that low perception of quality is related to negative emotions. Methodologically, our results indicate that Theta and Alpha frequency bands offer a means of studying cortical activation patterns during both cognitive and emotional information processing.

To investigate quantitatively whether the HDR image quality has a significant influence on the EEG frequency bands, an ANOVA analysis was performed on the subjective ratings, with a significance P-value threshold of 0.001. TABLE 4-3 summarizes the ANOVA results and beta gave a significant P-value < 0.001. Overall, the results of the ANOVA analysis revealed that beta has an impact on HDR perceived quality. However, the other interactions were not significant, P > 0.001. It has been established that beta band is highly associated with cognition thinking, and reflects emotional behaviour [43]. Our finding parallels that of Kroupi et al [2] which found that the beta frequency band significantly increased in the 3D environment, which received a significantly higher score in comparison to 2D video.

Table 4-3: ANOVA analysis

Source	dF	F	P-value
Delta	3	5.092	0.001668
Theta	3	5.342	0.001178
Alpha	3	5.356	0.001155
Beta	3	5.470	**0.000984**
Gamma	3	5.292	0.001263

4.4.4 The coupling measurements

To understand human behavioural states at the neural level, the coupling between delta and beta frequency bands was computed as the correlation coefficient between the mean powers in the frequency bands. This is linked with negative behavioural characteristics (anxiety, frustration, dissatisfaction). Clinical literature [2], [12], [16], [43], [148] indicates that increased EEG delta-beta coupling promotes behavioural inhibition states. This means that the closer the coupling (or correlation) is to 0, the more the subject would be satisfied with the test. On the other hand, as coupling or correlation approaches 1, the less the subjects like the HDR image (or the more frustrated they are frustrated by the test).

By calculating the coupling values between delta and beta for each tone-mapped HDR image quality of the results, high coupling values (e.g. greater than 0.5) would be considered to represent unsatisfied subjects (or subjects who had an unpleasant experience).

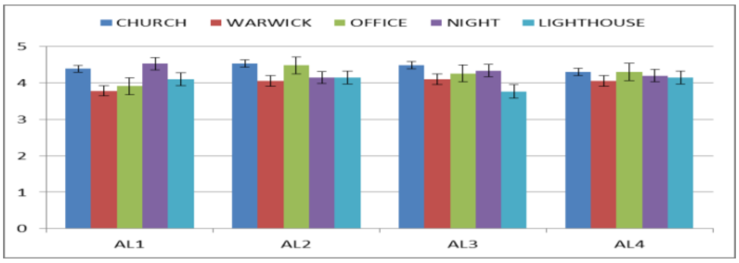


Figure 4-6: MOS and CIs for experienced TMOs after coupling

To explore this point, the scores for subjects who were unsatisfied were removed (7 out of 28) from the dataset. Figure 4-6 shows the MOS for the four quality levels for the five contents after removing those subjects. By comparing Figure 4-6 and Figure 4-4, we can see the MOS values per algorithm per content have increased. On the other hand, the Standard deviation and 95% confidence interval have decreased. The results suggest that it is sometimes difficult for participants to link the experienced quality to the quality scale in explicit tests and that EEG-based measure provides additional and complementary information, which aids understanding of human perception of the contents.

4.5 Summary

This chapter investigated the relationships between changes in EEG features and a QoE metric (i.e. MOS) for HDR images. 28 subjects viewed 20 HDR images during informal, subjective tests and the subjects' EEG data were also recorded and subsequently processed. To investigate quantitatively whether the HDR image quality has a significant influence on the EEG frequency bands, an ANOVA and Pearson correlation analysis was performed on the subjective ratings. We found that gamma, beta, and delta frequency bands gave the most discriminating correlation with MOS. Moreover, from the ANOVA results, the beta band gave a significant p-value < 0.001. Overall, the results of the ANOVA analysis revealed that changes in the beta had an impact on HDR perceived quality. The present results indicate that induced emotions have visible electrophysiological correlates with the content. Emotional activation paradigms in association with Electrophysiological measures represent a fruitful experimental avenue for future research by illustrating the biological correlates of emotions.

Chapter 5 EEG-based QoE model of human behaviour for mobile high dynamic range images

5.1 Introduction

To improve the quality of mobile HDR image services, research by academics and industry service providers have focused on developing QoE models to predict overall user-perceived quality to optimize quality provision [117]. However, modelling QoE is challenging due to the complex influences of user experience and diverse conditions of image content, context, and mobile devices [154]. QoE is necessary to understand how humans perceive quality from visual stimuli as this can be potentially exploited for developing and optimizing images and video processing algorithms [72].

The primary trend in mobile services today is towards HDR as seen with the introduction of the streaming-based services, e.g. mobile TV and photo applications. More the HDR content is being produced and its imminent adoption by the broadcast community means that there will soon be a demand for model HDR content on mobile devices[5], [155]. One of the most critical issues in mobile HDR image delivery services is how to maximize the QoE of the users for the delivered contents [35]. An open research question is how HDR images with different contents perform on mobile phones. Mobile devices, however, have certain differences compared to traditional viewing devices from QoE point of view. In particular, they are usually used “on-the-go,” making the context variables such as ambient lighting levels, or reflections important variables that need to be considered. Furthermore, despite their evolution so far, mobile devices usually have additional hardware limitations such as power supply, display features, or local storage availability [5],[101]-[103]. Traditionally, evaluation of the perceived quality of multimedia content is done using subjective opinion tests, such as MOS [157]. However, it is difficult for the user to link the experienced quality to the quality scale. Moreover, MOS does not give an insight into how the user really feels, at the physiological level, in response to dislikes or satisfaction with the perceived quality [72], [12], [61], [39]. To address this issue, measures which can be taken directly (implicitly) from the participant have attracted interest [10], [12]. At present, there is no standard for using electrophysiology to assess QoE, but contributions are being made to the ITU-T on the use of physiological measures for QoE (e.g. ITU-T Contribution COM 12-(039, 112, 103, and 202) [105], [130].

However, limited research has focused on establishing models to predict the user acceptance of mobile image [105]. On the other hand, modelling QoE is challenging due to the variability and complexity of human behaviour, as not all humans have similar preferences, feelings or perceptions about a particular service or product. However, limited research has focused on establishing models to predict the user acceptance of mobile image [154]. Furthermore, user perceptions and preferences continuously change over time. The challenge is how to better understand human behavioural states and transform them into meaningful data [158]. Generally, QoE models are constructed in three steps: (i) collecting subjective evaluation data; (ii) identifying critical elements influencing the subjective value; and (iii) determining the relationship between the subjective value and these elements

EEG features have shown to provide useful insights for QoE characterization. For example, the P300 event-related potential (ERP) signal, which occurs 300ms post-stimulus presentation, has been shown to be a useful EEG feature in characterizing the quality of text-to-speech (TTS), video, and audio-visual systems[1] [15]. EEG activity contains oscillations at a variety of frequencies. In EEG, five main different frequency ranges are ascribed to specific states of the brain: delta band (1–4 Hz), theta band (4–8 Hz), alpha band (8-13 Hz), beta band (13–30 Hz) and the gamma band (36–44 Hz) [122]. The delta band is present during deep sleep; the theta band occurs during light sleep and is an indicator of decreased alertness. Activity in the alpha band is related to relaxed wakefulness with eyes closed and a decrease in alertness. Beta and gamma band are ascribed to high arousal and focused attention [121]

Clinical research suggest that frequency coupling is a useful means of characterizing human emotions, mental activation status, and cognition. In [17-22] the delta and the beta frequency sub-bands have been linked to behavioural inhibition states (anxiety and frustration). In a pilot experiment (Chapter 4,[11]), we explored the usefulness of combining explicit and implicit features in viewing HDR images from the mobile device. It suggests that increased EEG delta-beta coupling promotes behavioural inhibition states. Thus, increases in the degree of coupling are associated with decreases in HDR quality. Motivated by these promising insights, in this chapter we highlight the main challenges in developing an EEG-Based QoE model of human behaviour for mobile High Dynamic Range Images. We show a novel process to collect user acceptance data through an iPhone, and adopt a nonlinear regression technique to develop mathematical QoE content dependent models for acceptability prediction based on the nature of the data fit curve. We adopted the statistical technique to find the QoE models that can generate the best-fitting estimate of the true acceptability curves. This aim is achieved by the following objectives:

- Subjective (explicit) tests, such as Mean Opinion Scores during HDR images quality assessment.
- EEG (implicit) test to understand the frequency components are related to HDR image quality perception in term of QoE.
- Investigate the relationships between the coupling between delta and beta frequency sub-bands to characterize human emotions such as anxiety and dissatisfaction.
- Different natural HDR image content with different Tone-mapping algorithms have been used in HDR image quality assessment.

In order to build the dataset required for modelling the QoE, we conducted a user study that involved a total of 28 participants, an iPhone mobile device and 40 (20X2) test stimuli from 5 HDR image sources.

5.2 Related work

Over the past years, there have been significant research efforts in the domain of QoE modelling aimed at finding the relationships between end-user QoE and psychophysical factors. Modelling QoE is challenging due to the difficulties in representing a complex subjective measure of user experience in a simple and objective way [110][159]. Fuzzy analysis has recently been shown to be of value in image quality assessment [160], [161]. Here, fuzzy regression models predict the psychophysical qualities in fuzzy numbers, which indicate both magnitudes and uncertainties of psychophysical data [162]. As such, they account for the variability of human responses in self-report, both within and across observers. In the context of physiological measures, these techniques may be able to capture the noisiness of the measurement device and, more importantly, the fuzziness of the physiological response, which can strongly vary between humans but also within humans depending on their current state and the given context.

Chen et al. [143] investigated visual fatigue for 2DTV and 3DTV viewing using 16-channel EEG measurements. Significant decreases in gravity frequency and power spectral entropy, related to alertness level decline, were observed in several brain regions after extended 3DTV viewing. Based on these findings and psychophysical responses, an accurate evaluation model for 3DTV fatigue was established. All bands except the rhythm changed significantly when subjects viewed 3DTV. In particular, the energy decreased in and frequency bands while activity increased significantly.

Machine learning [49] and related techniques such as support vector machines [163] and genetic programming [164] have been successfully used to predict QoE based on psychophysical responses. The power of these techniques is the discovery of patterns in the data that may otherwise be hidden. Recently, deep learning techniques, such as convolutional neural networks, have been shown to discover complex patterns in data at various scales. Not to be overstated, increased computing power and the collection of large numbers of training data has fuelled the recent jump in the predictive power of deep nets for computer vision and natural language processing applications. Similarly, as the number of psychophysiological training examples continues to grow, machine learning holds considerable potential to improve physiology-based QoE model prediction and generalization across use cases.

Yan Gong et al.[1] developed a QoE model with quantifiable metrics for QoE-based evaluation of service usage. They defined five QoE factors (usability, availability, service instantaneousness, service-integrity) however, they only focus on the relationship between QoS and QoE, considering neither the context nor the business domain. In addition, they do not differentiate QoE requirements based on various human roles and characteristics.

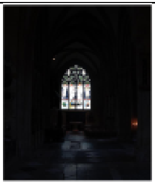
The ITU-T's G.1080 proposes a QoE model that classifies QoE factors into two parts: subjective human components and objective QoS parameters [7]. This model classifies the technical QoS parameters as part of the human objective QoE factor; whereas we believe that QoS could influence human behaviour like any other business factor (pricing), but it is not an inherent part of the human domain. QoE is a set of human-centric factors, not technology-centric parameters. Therefore, we are of the view that QoS is out of the human domain and is an external influencing factor.

5.3 Data collection

In this chapter, explicit subjective tests and implicit tests using the EEG were conducted. The study involved several participants viewing and rating the quality of

HDR images with different TMOs while their EEG data were recorded at the same time.

Table 5-1: Original HDR image description

	Original Image	Dimension	Histogram
Church (Indoor, no artificial lighting)		670X757	55.33
Warwick (Outdoor, day time)		1189X598	117.095
Office (Indoor, artificial lighting)		1165X751	115.65
Night (Outdoor, night-time)		1200X798	43.3375
Lighthouse (Outdoor, Sunset time)		1440X980	144.86

5.3.1 Tests stimuli

Five natural HDR scenes have been selected for this study, Church (Indoor, no artificial lighting), Warwick (Outdoor, day time), Office (Indoor, artificial lighting), Night (Outdoor, night-time), Lighthouse (Outdoor, Sunset time) Table 5-1, based on their visual content and quality, the dynamic range of the content was also among the selection criteria. These five images were processed by four TMOs [7]. A total of twenty HDR images has been viewed by the participants. The images were selected in such a way to have different representation in terms of content types (indoor or outdoor) and luminance range (night and day shots).

5.3.2 Experimental design

The subjective study was conducted in order to analyse if the proposed QoE-EEG in SSDs The study involved a number of participants viewing and rating the quality of HDR with different TMOs while wearing an EEG device headset. Table 5-2 shows an overview of the subjective experiment. The experimental design is explained in chapter 4, section 4.4.

Table 5-2: Overview of the subjective experiment.

Participants	
Participants Number	28
Male/female	15/13
Occupation	University postgraduate students
Average age	33.6
Environment	Laboratory setup Room
Device	
Monitor Type	IPhone 6
Size	4.7 inches
Resolution	1334×750
Stimuli presentation	
Number of images	20
Presentation order	Randomly
Viewing time	33 Sec

5.4 Mobile EEG-based QoE model

5.4.1 EEG-based QoE model based on regression technique

We used our dataset to highlight the main challenges in developing an EEG-Based QoE model of human behavioural for mobile High Dynamic Range Images. We show a novel process to collect user acceptance data through an iPhone, and adopt a nonlinear regression technique to produce mathematical QoE content dependent models for acceptability prediction based on the nature of the data fit curve. We adopted the statistical technique to find the QoE models that can generate the best-fitting estimate of the true acceptability curves.

After removing the unsatisfied subjects from the delta-beta coupling, the remaining dataset was divided into 60% and 40% for training and testing, respectively. The key aspect of this ratio is that we will have a high chance of getting all the target class detailed observation into the training dataset; this will be helpful in the modelling [165].

After dividing the dataset, we applied the 60% training data in the MATLAB Curve Fitting Tool. The remaining 40% of the testing for the entire five image scenarios is used for evaluation. The best fitting equation which worked on the five content scenarios was exponential with high R-square values. General Exponential model with Coefficients (with 95% confidence bounds): Based on the results, the MOS HDR values for HDR images can be modelled as:

$$MOS = f(CT, CP) \qquad (1)$$

Where CT is the content type and CP denotes coupling.

$$MOS = ae^{bx} + ce^{dx} \qquad (2)$$

Where, f (x) =MOS, a, b, c, and d are coefficients (c.f., Table 5-3) obtained from the regression fittings.

Table 5-3: Coefficients of proposed QoE model based content

Image	**Coefficients**			
	a	**b**	**c**	**d**
Indoor (no artificial lighting)	-1876	-2.535	1881	-2.528
Outdoor (Sunset)	3.615	5.375	1.986	0.937
Outdoor (night)	5.184	-1.17	5.16e-06	25.19
Indoor (artificial lighting)	644.4	-0.1816	-639.7	-0.178
Outdoor (day)	0.8005	-33.12	4.551	-0.851

5.4.2 Model evaluation

In order to evaluate the EEG-Based QoE Model (2), we used 40% for the dataset for validation for the entire five image scenarios. The accuracy of the model was determined by computing the R^2 and the RMSE. The R^2 correlations and RMSE for both training and validation dataset are illustrated in Table 5-4 and 5-5, respectively. Figure 5-1 depicts the scatter graph of subjective MOS values against the proposed model in (2).

Table 5-4: Evaluation of proposed QoE model based content (training dataset)

	Indoor (No artificial lighting)	Outdoor (Sunset)	Outdoor (Night)	Indoor (Artificial lighting)	Outdoor (Day)
R^2	0.914	0.834	0.908	0.809	0.912
RMSE	0.170	0.259	0.171	0.211	0.197

Table 5-5: Evaluation of proposed qoe model based content (validation dataset)

	Indoor (No artificial lighting)	Outdoor (Sunset)	Outdoor (Night)	Indoor (Artificial lighting)	Outdoor (Day)
R^2	0.8858	0.7798	0.8782	0.7458	0.8839
RMSE	0.1629	0.1184	0.1440	0.1192	0.1551

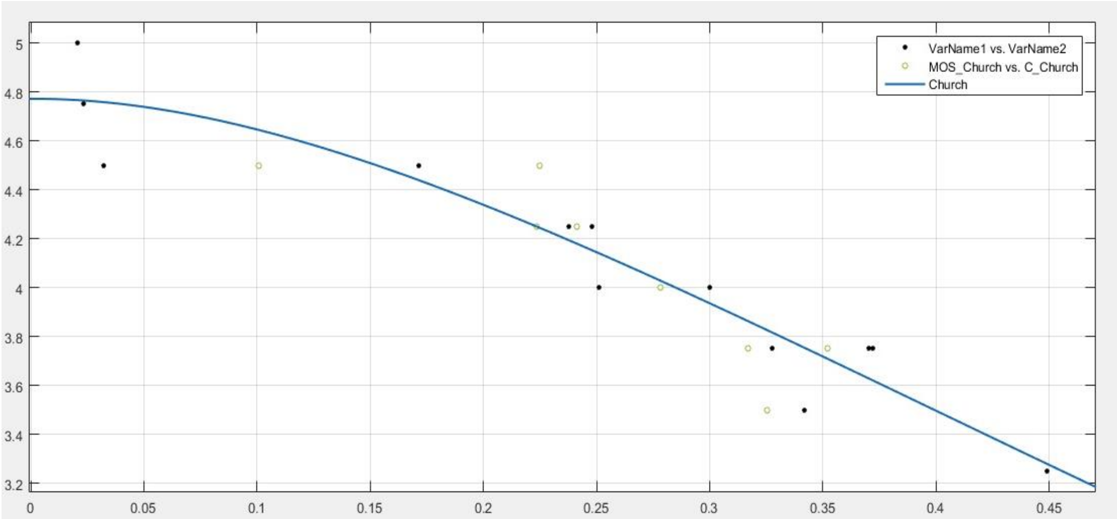
While our current experimental setup provides new and relevant information, there are also a number of limitations and challenges that exist in our method. First, the TMO arising in our HDR stimulus does not cover the full range of possible qualities. Thus, the quality characteristics of the used stimuli are only the highest quality. For a full assessment, several experiments have to be conducted to examine the different types TMO quality combinations.

Second, because of the relatively small size of dataset limited to natural scenes only, we need to expand our dataset in size and covering different contents types.

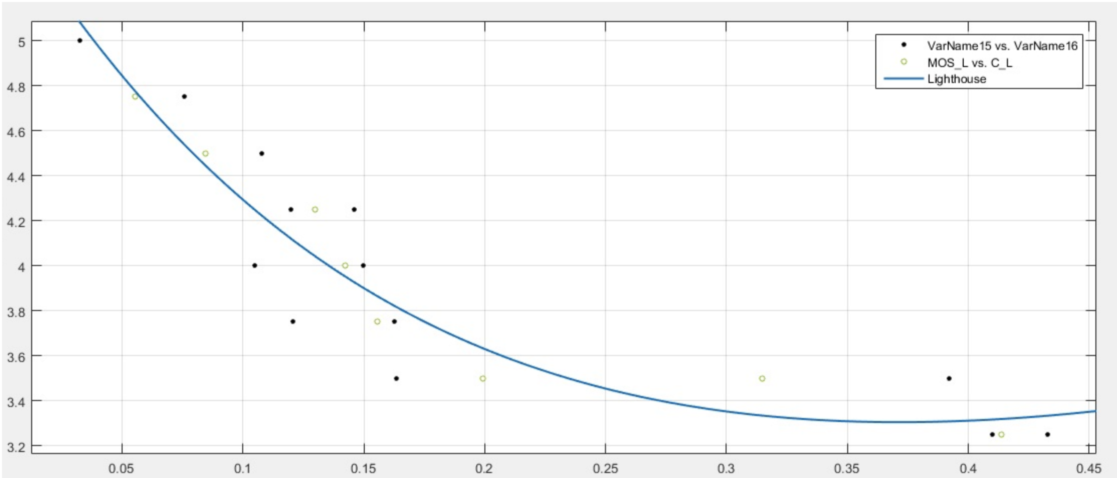
Third, the individual physiological difference between humans when using EEG, which may generate systematic errors between participants or groups, underscores another principle challenge for QoE assessment that is designed to be applicable to a general population.

In psychophysiological research, knowledge is derived about cognitive states from physiological measurements. It is important to understand the quality of the physiological response provided by the measurement tool used. Choosing the device is typically subject to a quality cost trade-off given the availability of a wide range of consumer, research, and medical grade physiological measurement devices. Numerous portable devices such as have been developed with the main aim to promote the usability of physiological measurements in real-world scenarios. While they usually come at low cost, the capabilities and quality provided are often limited. Research and medical grade physiological measuring devices come with a number of features but are associated with higher costs and often less flexibility. Rigorous studies are needed to fully understand the relationship of a broad range of physiological measurement devices and their impact on QoE assessment.

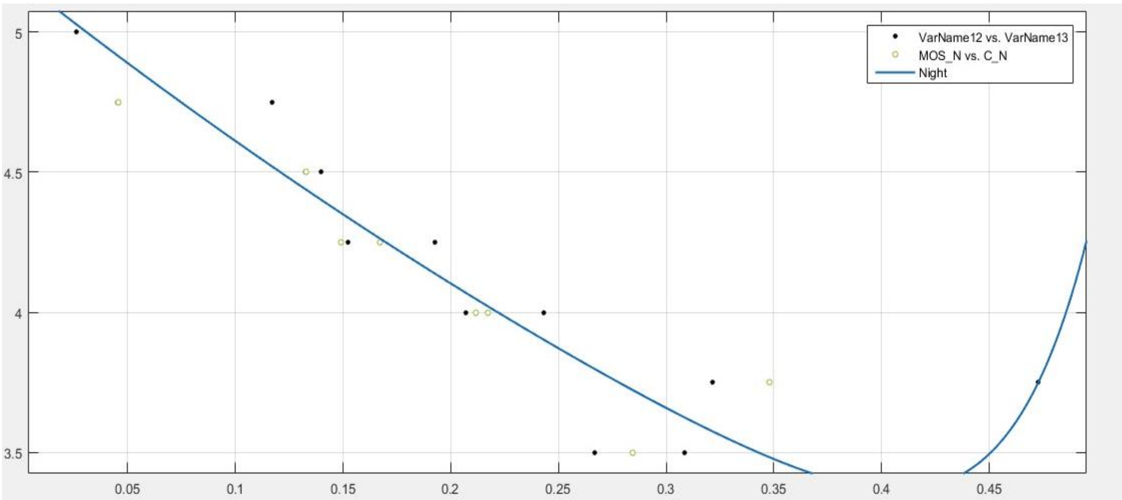
Fourth, attaching sensors to subjects can result in the subject feeling a certain degree of discomfort or otherwise change their natural behaviour. Moreover, experiments requiring attached sensors are often considerably more complex, such factors can have a direct impact on experiment duration and consequently, on the availability of participants.


VarName1 vs. VarName2
MOS_Church vs. C_Church
Church

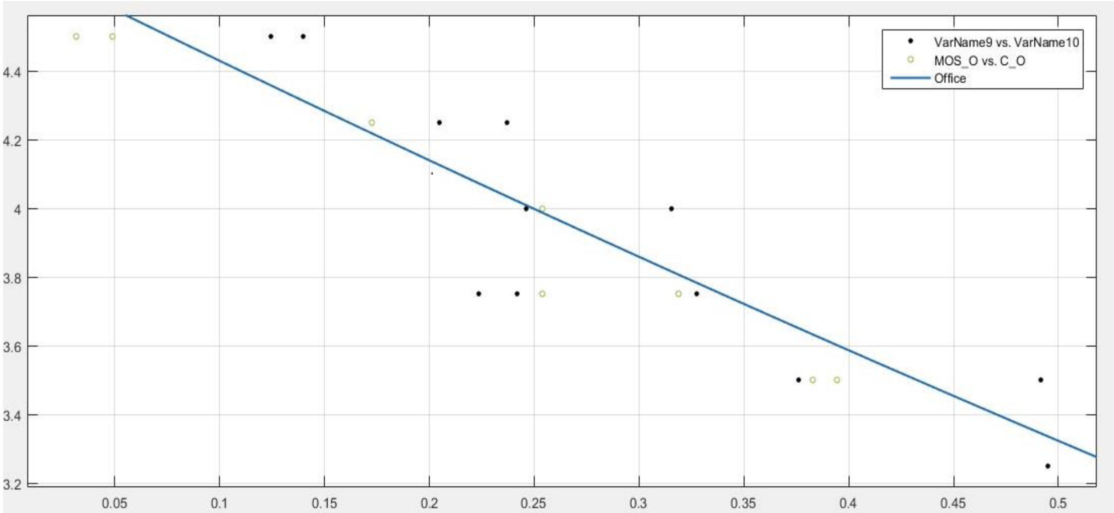
a


VarName15 vs. VarName16
MOS_L vs. C_L
Lighthouse

b


VarName12 vs. VarName13
MOS_N vs. C_N
Night

c



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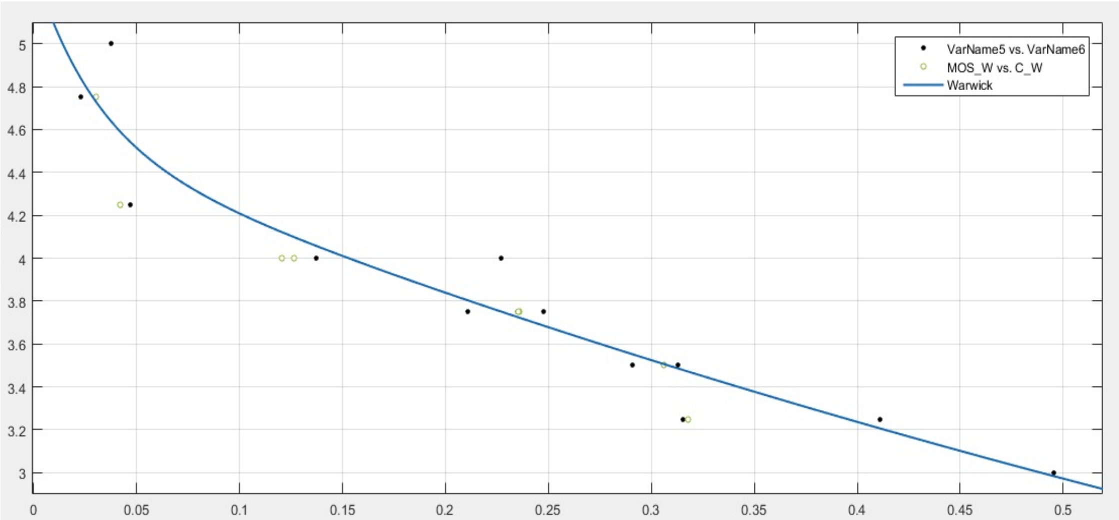

e

Figure 5-1: The scatter graph of subjective MOS values against the proposed model (a) Indoor (no artificial lighting), (b) Outdoor (Sunset), (c) Outdoor (night), (d)Indoor (artificial lighting), (e)Outdoor (day)

5.5 Summary

In this chapter, we have proposed a novel approach for mobile HDR image quality prediction using EEG features. QoE is a promising solution for mobile service providers, however, QoE measurement is challenging due to the variability and complexity of human behaviour, as not all humans have similar preferences, feelings or perceptions about a particular service or product. Furthermore, user perceptions and preferences continually change over time. The challenge is how to better understand human behavioural states and transform them into meaningful data.

Twenty-eight subjects viewed 20 HDR images during informal, subjective tests and the subjects' EEG data were also recorded and subsequently processed. We proposed a model, which has the potential to predict the user acceptance of mobile image, based on the coupling between delta and beta frequency bands. Delta-beta coupling provides information about user anxiety, frustration, and dissatisfaction. As such, if content and service providers want to ensure a rich quality of user experience, the coupling should not be strong enough to incite negative behavioural characteristics in end users.

Chapter 6 A New method to detect Colour Vision Deficiency Using the EEG and High Dynamic Range images

6.1 Introduction

Colour Vision Deficiency (CVD) refers to a variety of colour perception disorders. CVD rarely results in a complete lack of colour vision but instead manifests itself as an inability to detect differences in colour that can be readily distinguished by a normal colour observer [166]. It affects approximately 8% of men and 0.5% of women in the world [26]. In the UK, there are approximately 2.7 million CVD people (about 4.5% of the entire population). This means that about 450,000 children in the UK or one child in every classroom cannot identify many different colours, only red and green [30]. For most cases, CVD is an inherited condition, with males much more likely to have CVD than females because the genes responsible for the most common, inherited colour blindness is on the X chromosome [26][30]. CVD can also be acquired through different factors such as ageing or brain injury, and it can also be a symptom of conditions such as attention-deficit/hyperactivity disorder (ADHD), Parkinson's disease (PD) and epilepsy [167]. There are three different types of CVD (i.e. Monochromatic, Dichromatic, trichromatic) all of which have a direct relation to the photoreceptors in the visual system.

CVD can cause many real-life problems, ranging from minor frustrations, such as difficulty with buying fruits, cooking meat, identifying children's toys, enjoying the visual arts, and decorating [46]. It also has health and safety implications (e.g. when alert messages do not stand out from the background) and may affect professional lives [4]. Visible signs and symptoms of inherited CVD may be found in children with poor vision and intolerance to bright light at a very young age. This is why it is suggested that children who have trouble in school should be evaluated for vision problems, including CVD [168]. Milder forms of CVD are subtler, and many people never realize that they have a problem seeing colours. It is not uncommon for a diagnosed colour blind child to have been prescribed spectacles, but not screened for CVD [26] [28] [45]. As a result, approximately 40% of colour-blind pupils currently who leave secondary school are unaware that they suffer from CVD.

Therefore, it is important to routinely test all children for colour vision in order to identify those with CVD at an early age. Currently, there is no cure for CVD, but those with CVD can improve coping strategies to get around the problems effectively [46]. Furthermore, they may use special lenses to assist them to distinguish colours more precisely, but these are only useful for outdoors and under bright lighting conditions. There are tablets and smartphones applications (Apps) that can help people with CVD to distinguish between colours [46]. More sophisticated Apps allow users to find out the shades of colours [169] [166]. Although these methods can help people with CVD, the condition should be diagnosed first.

The standard CVD test is the Ishihara plate test that is dependent on which numbers children can see from coloured dots that are set within a circle formed of dots of different colours [28]. A major limitation of this test is that it cannot be used to screen children who cannot say which numbers they can see. For example, children who rely on eye gaze cannot be accurately tested for CVD at present [45]. Other detection methods exist, but these also have their own limitations (e.g. cost per examination, minimum age that can be tested with) [170]. Moreover, only the Ishihara plates are considered suitable for screening a large number of persons over a relatively short period of time [171]. Research has shown that diagnosis of up to 1/3 of the CVD patients is not informed by the characteristics or type of subject-specific colour vision disorder [170] [171]. However, colour vision testing is not a statutory element of the NHS eye examination in England, and studies show that by the year 7 about 80% of pupils have never had a CVD test [30], [45]. It is common for a diagnosed colour-blind child to have been prescribed spectacles, but not screened for CVD. Opticians can offer a free test, but, because it's not part of the eye test, parents and carers may have to ask for it [2] [8].

Given the number of people affected by CVD, there is a need for a low-cost method to detect CVD. Potentially, the electroencephalogram (EEG) can fulfil this need. We hypothesise that changes in the visual system and brain due to CVD may be reflected in the electrical activity of the brain, the EEG when subjects view certain multimedia content such as HDR images and that these changes can be quantified as a biomarker. The EEG is non-invasive, low-cost, has a high temporal resolution and provides valuable information about brain dynamics [17], [18], [19], [20], [21], [22], [23]. In recent years, the use of the EEG to assess Quality of Experience (QoE) of multimedia content has attracted a great deal of interest.

Traditionally, perceived QoE of multimedia content is assessed using subjective opinion tests, such as Mean Opinion Scores (MOS). However, MOS does not give an insight into how the user really feels, at the physiological level, in response to dislikes or satisfaction with the perceived quality [3]. The use of the EEG aims to address this issue. The emotional responses to multimedia content have been investigated frequently, using the spectral power of EEG signals. Ko et al. [172] investigated the relative power of the alpha, beta, gamma, delta, and theta frequency bands to build an emotional recognition system induced by videos (joy, neutral, anger, sadness, and surprise). Kroupi et al. [127] investigated the power of the EEG frequency bands (alpha, low beta, middle beta, high beta, gamma, and theta), and their correlation with subjective quality in exploring the implicit monitoring of QoE of 2D and 3D videos. They found the frontal asymmetry patterns in the alpha band are related to the perceived quality. Perez et al. [148] used EEG to measure the brain activity for classifying pictures into high and low-quality pictures. These studies demonstrate that quality changes in images, audio, and videos can be successfully detected by observing brain activities.

HDR images represent a wide range of luminance levels, which reproduce realistic and visually appealing content that can represent the different shades of colour and amount of light in images that is close to reality. When HDR images are viewed and subjects are assessing image quality, this may cause changes in the EEG, which may be associated with CVD. Changes in the EEG due to CVD can be accentuated when viewing HDR images. HDR imaging is used in many applications to create visually pleasing images especially scenes that containing very bright, direct sunlight to extreme shade, or very faint shades, such as indoor parts and outdoor scenes [24], [61]. In practice, HDR images are converted to Low Dynamic Range (LDR) images so that they can be viewed on standard devices using TMOs [24], [63], [93], [4]. Nowadays, mobile devices- known as small screen devices (SSDs) are becoming the main platform for the consumption of multimedia and the rapid increase in the number of such devices. With the ability and convenience to be used anywhere and at any time, smart mobile devices have become the main means for receiving imaging [68].

The aims of this study are twofold. Firstly, to investigate the relationships between changes in the EEG of CVD patients when viewing HDR images with SSD. Secondly, to propose a new method to detect CVD from the EEG and HDR images. We invoked changes in the brain activity due to CVD by showing subjects HDR images.

6.2 Investigation of the relationships between changes in the EEG and CVD- materials and methods

The objective in this section is to investigate the relationships between changes in the EEG and visual QoE in CVD subjects whilst viewing HDR images to provide the basis for detecting CVD. Although, there have few studies done regarding the evaluation of HDR image quality using EEG measurements for normal people, no work has hitherto been reported in the literature for CVD subjects. In this section, explicit subjective tests using the EEG were conducted. The study involved normal and CVD participants viewing and rating the visual quality of HDR images while their EEG data were recorded at the same time. Power spectral analysis of the EEG activity is used to quantify the changes in the EEG.

6.2.1 Data collection

Forty subjects were involved in the study, the subjects were students and staff at Plymouth University, UK, and all had a clear understanding of the test. Twenty subjects were colour blind (19 male and 1 female) and 20 were controls (17 male and 3 female). All were all right-handed and in the age range, 18-45 years. All the CVD subjects had Red-green colour blindness.

Before each experiment, a training session was given to allow participants to familiarize themselves with the procedure. The images used in the training session were different from the test images. The Research Ethics Committee at Plymouth University approved the study protocol. A portable EEG device (HeadCoach™, Alpha-Active Ltd, Devon, UK) [173] was used to record scalp EEG, with a sampling frequency of 128 Hz, bandpass hardware filter of 1-32 Hz, from two active (positive inputs) electrodes, placed on Fp1 and Fp2 according to the 10-20 EEG system [174]. Three additional electrodes were used, a passive Driven-Right-Leg (DRL) reference electrode [174] and two active (negative inputs) Common Mode Sense (CMS) electrodes, placed at Fpz and M1/M2 (mastoid process), respectively. DRL and CMS electrodes were used in order to reduce participant's electromagnetic interference and to improve the common-mode rejection ratio of the two recording positive input channels. Before electrode placement, the skin was prepared with an abrasive skin preparation gel (Nuprep™, Weaver, and Company, and Aurora, USA) and then cleaned with an alcohol-free wipe.

6.2.2 Test setup

Five HDR images were selected for the study, based on their visual content, quality, and dynamic range. The five images were each processed by four TMOs, giving a total of 20 HDR images, the test sequences and quality ratings were displayed on a website specially designed for [175]. Four different quality TMOs were used [45], these were logarithmic, iCAM06, Photographic Reproduction, and Bilateral Filtering. Figure 5-1 illustrates the set-up of the test. An iPhone 7 device running on IOS 10.3.1 operating system was used in the experiment. LED-backlit IPS LCD, capacitive touchscreen, 16M colours, size 5.5 inches, resolution 1080 x 1920 pixels with 16:9 ratio was used. An Intel Core™ i7 PC running Microsoft Windows 7 Enterprise operating system was used to process the EEG data. The iPhone and the EEG recording PC were time synchronized to facilitate the data analysis.

Two separate experiments were conducted. Each experiment involved two groups, containing twenty persons each. One group consisted of people who had already been diagnosed with colour-blindness, while the second group consisted of people with normal colour vision. Two sessions were assigned for each experiment, and 20 colour and 20 greyscale stimuli images were displayed on the device to each session. Half an hour break was given between the two sessions to prevent lack of attention and fatigue and to ensure comfort. Each session lasted approximately half an hour, excluding the training and the setup of the EEG devices. Each trial consisted of a 30-second baseline phase. During the baseline period, subjects were instructed to remain calm and to focus on a 2D white cross on a grey background presented on the screen in front of them. The EEG signals recorded that was during the baseline period were used to remove stimulus-unrelated variations of the signals acquired during the stimulus period. Once the baseline period was over, an HDR image stimulus was presented randomly for 30 seconds. At the end of this, subjects were asked to provide their ratings for the HDR image stimulus within 60 seconds. After the participant has submitted the rating, the next stimulus appears on the SSD, with the order of sessions and trials randomized. Subjects were asked to evaluate the HDR stimuli, using a discrete five-level rating scale (ITU-R quality ratings) [26].

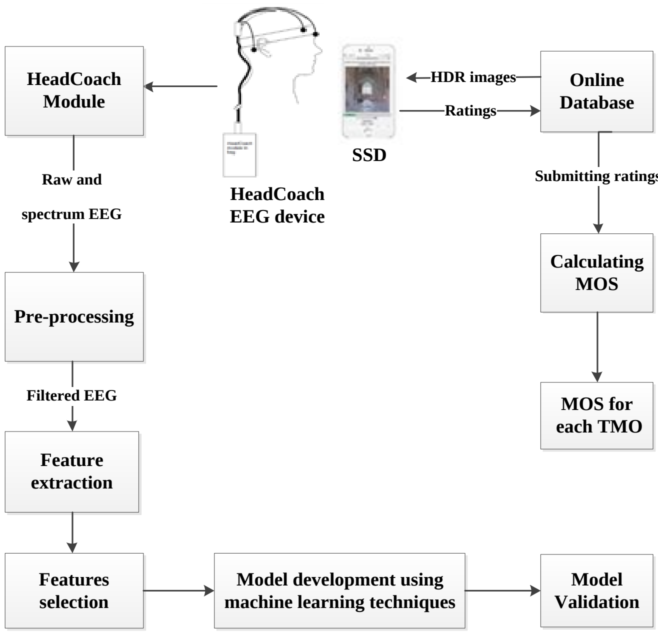

Figure 6-1: Set-up for the test

6.2.3 Methods

In our approach, the subjective results are taken as ground truth and are used as a basis for the power spectrum analysis. The following steps summarise the procedure that was used in the subjective assessment.

1. MOS scores were computed for normal and CVD subjects, with the MOS values representing the average subjective quality ratings across all participants.
2. The 95% Confidence Interval (CI) was determined for all HDR images.

In our approach, the complete recordings of the EEG including artefacts were used without a prior selection of elements for analyses to allow us to have an idea about the robustness and usefulness of the method in practice. Data from a fixed interval (4s to 33s) was used to avoid electrical artefacts, which often occur at the beginning of a record, leaving a standard 30 seconds data to analyse. The following steps summarise the procedure that was used to derive the changes in the power spectrum (PS) of the EEG signal.

1. The EEG signal was filtered using Infinite Impulse Response (IIR) Chebyshev-II bandpass filters into five frequency bands (*i.e.,* delta 0-4Hz, theta 4-8Hz, alpha 8-13Hz, beta 13-30Hz, and gamma 30-60Hz). A low computational IIR filter was used for computational efficiency [176].
2. The PS for each EEG band was computed for each subject.
3. The power spectrum of the baseline was subtracted from the power spectrum for each subject. This was provided negative PS values in some cases.
4. All the PS values were normalised to lie in the zero to ten to make it easier to visualise and compare the PS.

Power spectrum (PS): PS [177] computation of an N-sample EEG data sequence x(1), x(2), ..., x(N), was computed based on magnitude squared of the Fast Fourier Transform (FFT) ,

$$PS_{X(N)} = [|FFT(X(N)|]^2 \tag{1}$$

The PS was computed for the traditional EEG frequency bands (*i.e.,* delta, theta, alpha, beta, and gamma). We computed 40 features for each subject (five EEG frequency bands multiplied by eight HDR images), 20 features for HDR colour images, and 20 features for HDR greyscale image analysis.

6.3 Results

6.3.1 Subjective assessment

Typically, subjective quality assessment involves individual quality ratings, and the final result is then expressed as MOS, that is the average of the individual scores. The MOS scores were obtained and the EEG data recorded during the test. MOS representing the average subjective quality ratings across all participants are represented on nominal scales together with the associated 95% Confidence Interval (CI) for all HDR images. We chose a discrete five-level rating scale (ITU-R quality ratings), which is suitable for naïve observers (non-experts in image processing) and is relatively easy for them to use it to quantify quality ('5=Excellent' and '1=Bad') [178].

In the subjective test, we were trying to answer the research question, which is: How the MOS results are different between normal and CVD in Colour/Grey HDR images.

The results of the subjective assessments to colour HDR images are given in Figure 6-2 for normal and CVD subjects by using four different TMOs. These show that that the MOS values for normal subjects were higher than those for CVD subjects across the four TMOs

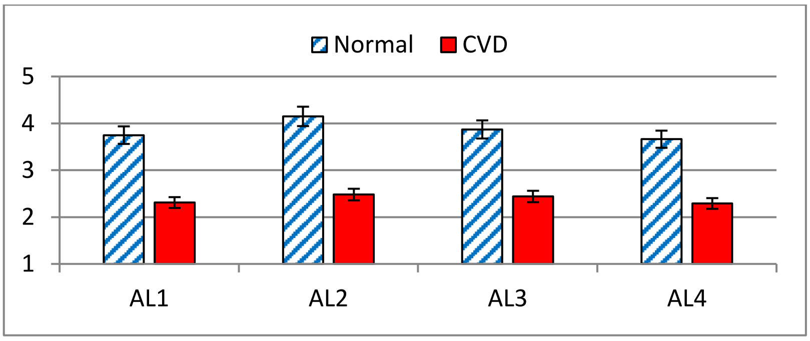

Figure 6-2: MOS results for colour HDR images for normal and CVD subjects

The results for greyscale HDR images are shown in Figure 6-3. These show that for greyscale HDR images there is little difference between the MOS values for normal and CVD subjects. This suggests that normal and CVD subjects respond in the same way to greyscale HDR images unlike in colour HDR images. Intuitively, this is to be expected given that colour deficiency is the main issue. The subjective assessment findings, represented by MOS, will be employed as the ground truth of perceptual quality assessments in order to ensure the correspondence with perceived quality, which already showed a difference in the results for colour images.

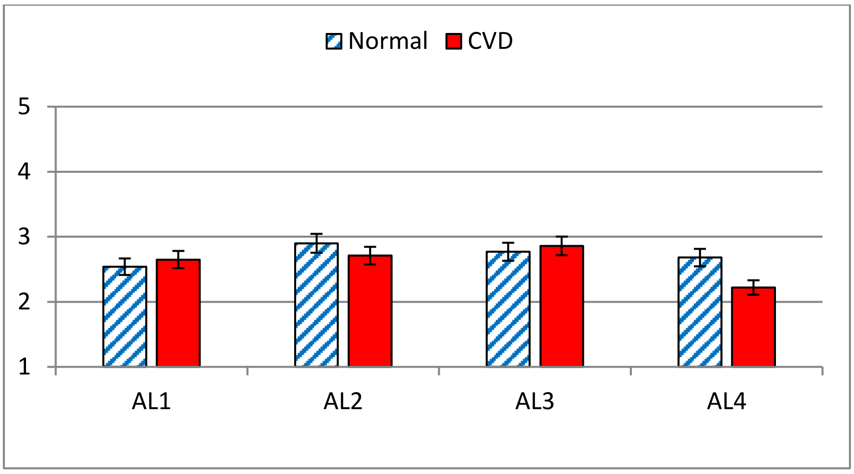

Figure 6-3: MOS results for greyscale HDR images for normal and CVD subjects

6.3.2 Power spectrum analysis

Figures 6-4 and 6-5 show shows the mean spectral power in the five EEG bands for CVD and normal subjects in colour and greyscale HDR images, respectively. The results show that for both colour and greyscale images there are significant differences in the spectral power between CVD and normal subjects in all five EEG bands, and particularly so in the delta, theta and alpha bands. This difference may be suitable for quantifying changes in EEG due to CVD as they may be capable of being used to discriminate between CVD and normal subjects. This suggests that PS analysis may be suitable for quantifying changes in the EEG due to CVD and, potentially, may provide a basis for detecting CVD subjects.

We note that, unlike in the MOS results above, there are significant differences in the spectral power between normal and CVD subjects for both colour and greyscale HDR images.

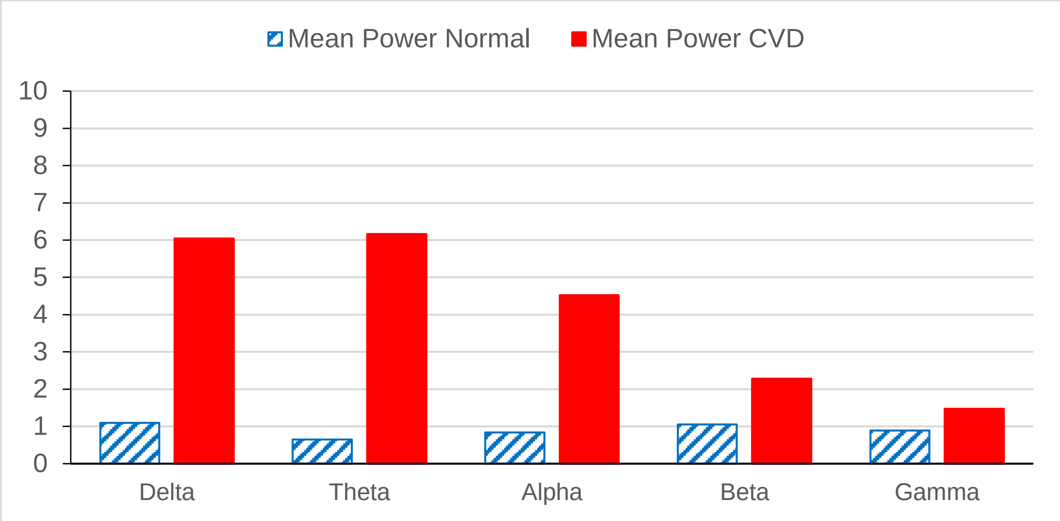

Figure 6-4 : PS for CVD and normal subjects for colour images

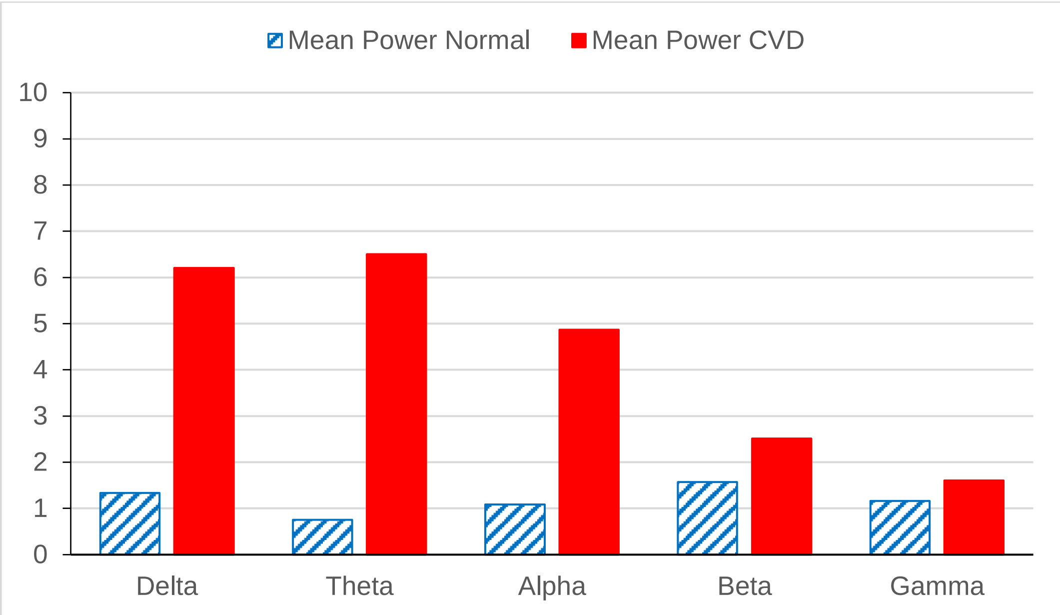

Figure 6-5:PS for CVD and normal subjects for greyscale images

Table 6-1: Mean power in colour and greyscale images for both normal and CVDs

	Colour HDR		Greyscale HDR	
	Mean Power Normal	**Mean Power CVD**	**Mean Power Normal**	**Mean Power CVD**
Delta	1.09723235	6.03950282	1.33558447	6.20865897
Theta	0.6484424	6.16091634	0.75442672	6.50052252
Alpha	0.8346584	4.52031891	1.08890715	4.86896785
Beta	1.055600875	2.27804075	1.56877823	2.51595025
Gamma	0.892905475	1.47583027	1.16597425	1.60327812

Figure 6-6: A Comparison between the way that normal and CVD subjects are viewing the test images

6.4 Proposed new approach for the detection of CVD condition

The results of the subjective assessment show that there are significant differences in the MOS values for colour and greyscale HDR colour images emerged a significant difference between normal and CVD subjects as shown in Table 6-1, while the greyscale HDR images showed a little difference between them as shown in Table 6-1. To visualize the differences in EEG signal between CVD and normal subjects, p-values were computed between them by using Welch's t-test. P-values between the CVD and normal subjects were computed to define which EEG features have a significant association with CVD and may be used in CVD detection.

6.4.1 P-values analysis

P-values were analysed for EEG signal for CVD colour and greyscale HDR images. For colour HDR images, four out of the five frequency bands achieved a significant p-value<0.001 Overall, the results of the P-values analysis revealed that delta, theta, alpha, and beta bands have an impact on the perceived quality HDR colour images, especially, theta with a very low p-value< 10^{-9}. However, gamma interactions were not significant. Table 6-2 shows p-values between CVD and normal subjects for HDR colour images.

Table 6-2: P-VALUES BETWEEN CVD AND NORMAL SUBJECTS FOR HDR COLOUR IMAGES

	Delta	Theta	Alpha	Beta	Gamma
P-value	1.993E-08	8.506E-09	8.660E-07	4.571E-03	1.124E-01

For greyscale HDR images, three out of the five frequency bands achieved a significant p-value<0.001. The results of the analysis revealed that delta, theta and alpha bands have an impact on HDR greyscale image perceived quality, especially, alpha with a very low p-value<10^{-10}. However, beta and gamma interactions were not significant. Table 6-3 shows p-values between CVD and normal subjects for HDR greyscale images.

Table 6-3: P-VALUES BETWEEN CVD AND NORMAL SUBJECTS FOR HDR GREYSCALE IMAGES

	Delta	Theta	Alpha	Beta	Gamma	
P-value	9.544E-10	3.965E-09	1.368E-06	5.185E-02	2.708E-01	

Tables 6-2 and 6-3 show the p-values between CVD and normal subjects for HDR colour and greyscale images. We can conclude that; I) the Delta and theta band is significantly lower in CVD in both colour and greyscale images with the other EEG frequency bands, II) Alpha band p-value is significant in both colours and greyscale images, III) The Beta band is more in colour than greyscale images, Finally, IV) The p-value of gamma band in both colour and greyscale image is > 0.001 which is not significant.

6.4.2 Model development

Our finding shows there is a significant difference in EEG signal power between CVD and normal subjects. To investigate how the findings may be used in practice used machine learning techniques to develop a method that can be used to detect CVD subjects.

We developed a machine learning-based model to distinguish between CVD and normal subjects using EEG spectral features. Support vector machine (SVM) was used as a classifier for the model of CVD. SVM has shown good performance in the analysis of biomedical data [179], [180], [181]. It has a stable classification performance and outperforms most other machine learning techniques (e.g., Multilayer Perceptron, Bayes Network, and Logistic Regression) [179], [180], [181], [182].

The EEG dataset was divided into training and testing datasets (60% for training and 40% for testing) with subjects selected at random. We selected 24 subjects for training and 16 subjects for testing at random from the data sets. The training data included 12 CVD and 12 normal subjects, while the testing data include eight CVD and eight normal subjects. P-values were computed using the training EEG dataset to determine the EEG features that have a significant association with CVD.

The performance of the CVD detection model was assessed in terms of sensitivity (Sen), specificity (Spec), accuracy (ACC), F-measure, false negative rate (FNR), false positive rate (FPR), positive predictive value (PPV), and negative predictive value (NPV). Matthew's correlation coefficient (MCC) was computed to measure the quality of the binary classification (CVD and normal) between the actual and predicted results [183][184].

The testing dataset was used to compute the performance of the SVM model that was developed based on PS of the training dataset for the five EEG frequency bands. Table 6-4 shows the performance of diagnosing between CVD and normal subjects based on

PS analysis of the EEG signal of colour HDR images for all the EEG frequency bands. Delta, theta, gamma and alpha band's performance were significant for sensitivity and specificity. Sensitivity represent the ratio of CVD subjects and the model diagnosed them as CVD, Specificity represent normal subjects been diagnosed as normal by the model. While Accuracy represent is the total subjects that diagnosed accurately, which is combined Normal and CVD subjects. In addition this is a pilot study, with limited number of subjects, 28, which is compatible to ITU-R recommendation (>15 subjects) To check the performance of any diagnostic model, needs to check both Sensitivity and Specificity in one time or Accuracy only.

Table 6-4: PERFORMANCE DIAGNOSIS OF CVD SUBJECTS FOR HDR COLOUR IMAGES

Performances	Delta	Theta	Alpha	Beta	Gamma
Sensitivity	83.33	100.00	100.00	80.00	100.00
Specificity	90.00	90.91	83.33	81.82	66.67
Accuracy	87.50	93.75	87.50	81.25	68.75
F_measure	83.33	90.91	80.00	72.73	28.57
MCC	73.33	87.04	74.54	59.19	33.33
FPR	10.00	9.09	16.67	18.18	33.33
FNR	16.67	0.00	0.00	20.00	0.00
PPV	83.33	83.33	66.67	66.67	16.67
NPV	90.00	100.00	100.00	90.00	100.00

Table 6-5 shows the performance of diagnosing between CVD and normal subjects based on PS analysis of the EEG signal of greyscale HDR images for all the EEG frequency bands. The significance performance of delta, theta, and alpha bands is to perform one for sensitivity and specificity.

Table 6-5: PERFORMANCE DIAGNOSIS OF CVD SUBJECTS FOR HDR GREYSCALE IMAGES

Performances	Delta	Theta	Alpha	Beta	Gamma
Sensitivity	100.00	100.00	100.00	75.00	66.67
Specificity	90.91	90.91	90.91	75.00	69.23
Accuracy	93.75	93.75	93.75	75.00	68.75
F_measure	90.91	90.91	90.91	60.00	44.44
MCC	87.04	87.04	87.04	44.72	28.94
FPR	9.09	9.09	9.09	25.00	30.77
FNR	0.00	0.00	0.00	25.00	33.33
PPV	83.33	83.33	83.33	50.00	33.33
NPV	100.00	100.00	100.00	90.00	90.00

The performance of the model suggests that it could be used in practice, after further development, to detect CVD. This would involve the following steps after the model has been trained:

Ask subject to view and rate a number of HDR images and record their EEG signal.

1. Pre-processing the recorded EEG signal (e.g.by subtracting the recorded EEG from the baseline).
2. Extract relevant features from the subtracted EEG (e.g. spectral powers)
3. Apply features of the model and classify subjects to determine whether the subject is normal or has CVD, with appropriate confidence level indicated.

6.5 Discussion

To the best of our knowledge, this is the first study to use the EEG signal and HDR to detect CVD. The results show that PS analysis of EEG provides a potentially reliable way to detect CVD subjects given the significant difference in the spectral power for CVD and normal subjects (see Table 6-1). For both colour and greyscale HDR images, a characteristic feature in the EEG of CVD subjects is the significant increase in the spectral power in the Delta, Theta, and Alpha bands (see Figure 6-4 and 6-5 and Table 6-1). The difference in the spectral power in the beta and gamma is not significant relatively speaking. The results suggest that when viewing HDR images CVD subjects respond in a different way to normal subjects for both colour and greyscale HDR images.

From the literature, in practice, delta activity is more pronounced during sleep, whereas theta oscillations have been found to be closely correlated with memory processes and is an indicator of decreased alertness. Alpha activity is related to relaxed wakefulness with eyes closed and a decrease in alertness. The beta band is ascribed to high arousal and focused attention. Gamma band has been associated with multiple sensory and cognitive processes, especially memory functions are closely correlated with oscillations in the gamma band [11], [12], [127], [185], [186], [187].

In studies by Anton et al., participants were exposed to high quality and low-quality sequences of auditory material. Their only task was to rate the content on a scale every few minutes, and for the rest of the time, they should focus on the presented content. Higher values in the alpha band power were observed when being exposed to low-quality stimuli compared to higher quality stimuli, which is ascribed to fatigue and impaired information processing [22]. Arndt et al. [43] conducted two studies in which longer stimuli that were equivalent to documentaries have been used; the documentaries showed sea life scenes. In the first study, for the audio only scene-related background noise was present. One half of the audiovisual material was presented in the high-quality video and the other half in the low-quality video. The second study had an accompanying background narrator that was constantly talking. Here, both modalities were presented in their original quality as well as in reduced quality, either only one or both modalities were distorted, leading to four different quality levels. Within both studies, the state of the test participants and how it changed, presenting changes different quality levels were analysed. For the EEG data, a frequency power band analysis was performed. In both studies, it could be shown that an increase in alpha and theta level is the result of a reduction in quality and this is could be correlated with how CVD reacts to images. Compared with standard literature in neuroscience, this increase is due to an increased level of fatigue and/or drowsiness.

Moreover, in Figure 6-2 for the MOS subjective results of colour HDR images, we observed the following: Normal subjects gave higher MOS than CVDs. Figure 6 shows a comparison between the way that normal and CVD subjects are viewing the test images this would give a clue and may support the fact that CVD subjects are viewing images and perceive colours in a different way than normal subjects and this will affect their MOS.

The response (MOS) of CVD subjects to the greyscale HRD images was close to that of normal subjects (See Figure 6-3). CVD subjects reacted nearly in the same way as normal subjects reacted to greyscale images. Therefore, HDR colour images have a significant performance than in the HDR greyscale images.

For the EEG analysis, we found that generally, all the frequency bands are higher in CVDs than normal for colour and greyscale HDR images. Moreover, delta, theta and alpha bands into colour HDR images are significantly higher in CVD than normals. Thus, PS analysis could provide a basis for developing an accurate, low-cost and easy use tool to detect CVD condition.

Overall, the results of the P-values analysis revealed that delta, theta, alpha, and beta bands have an impact on the perceived quality HDR colour images. While, the results of the analysis revealed that delta, theta and alpha bands have an impact on HDR greyscale image perceived quality.

For the colour HDR, normal subjects gave higher MOS than CVD subjects. For grey HDR images, the MOS results in normal subjects and CVD subjects were very close.

This suggests that normal and CVD subjects respond in the same way to greyscale HDR images. Our results show that CVD may cause changes in the EEG due, perhaps, to the lack of colour vision and an inability to detect the differences between the colours. We analysed the PS for greyscale and colour HDR images for the traditional five EEG frequency bands and gamma/theta ratio.

In colour HDR images, we found there is a wide range in PS between CVD and normal subjects, especially for delta, theta and alpha bands; they were higher in CVD than in normal subjects. The results suggest that the analysis of the EEG power spectrum may provide an accurate and reliable method to detect CVD. For greyscale HDR images, the results show that all the PS went a bit higher for both CVD and normal subjects and in the same sequence. This suggests that the EEG power spectrum may provide an accurate and reliable method to detect CVD from normal subjects.

Based on the findings, we developed a new method to detect colour vision deficiency using the EEG and HDR images. We used power in the bands and their ratios as candidate features for the development of a model to diagnose CDV with high sensitivity and specificity. We used machine learning techniques to select a number of features (power in the bands) whose combined diagnostic value is high in detecting CVD. Machine learning techniques were used in the classification of CVD and normal subject.

6.6 Summary

CVD is the inability to distinguish the differences between certain colours. CVD can cause many real-life problems, ranging from minor frustrations to difficulties that affect safety. In this paper, we proposed a new method to detect CVD from the EEG and HDR images by investigating the relationships between changes in the EEG of CVD patients when viewing HDR images. We invoked changes in the brain activity due to CVD by showing subjects HDR images, this is based upon the fact that HDR images can capture real-world scenes.

Twenty colour and twenty greyscale HDR images were viewed by 40 subjects (20 normal and 20 CVD) on SSD and submit their ratings while their brain activity was recorded by EEG. For the colour HDR, the MOS results we can see that normal subjects gave higher MOS than CVDs. For grey HDR images, MOS results in normal subjects and CVDs were very close. This suggests that normal and CVDs react in the same way to greyscale HDR images. Our results show that CVD may cause changes in the EEG due to the lack of colour vision and an inability to detect the differences between the colours. We analysed the PS for greyscale and colour HDR images for the traditional five EEG frequency bands and gamma/theta ratio.

In colour HDR images we found there is a wide range in PS between CVD and normal subjects, especially for delta, theta and alpha bands, they were higher in CVD than in normal subjects. Furthermore, the ratio between the gamma and theta for normal and CVD subjects was investigated in the study. In colour HDR, the gamma/theta ratio in CVD subjects is much lower than the ratio in normal subjects. The results suggest that the analysis of the EEG power spectrum may provide an accurate and reliable method to detect CVD. For greyscale HDR images, the results show that all the PS went a bit higher for both CVD and normal subjects and in the same sequence. This suggests that the EEG power spectrum may provide an accurate and reliable method to detect CVD from normal subjects.

Based on the findings, we developed a new method to detect colour vision deficiency using the EEG and HDR images. We used power in the bands and their ratios as candidate features for the development of a model to diagnose CDV with high sensitivity and specificity (target of 100%). We used machine learning techniques to select a number of features (power in the bands) whose combined diagnostic value is high in detecting CVD. Machine learning techniques (i.e., support vector machine) were used in the classification of CVD and normal subject. Sensitivity and specificity were computed to measure the performance of the power analysis of EEG in diagnosing of CVD. Delta, theta, and alpha bands are to perform one for sensitivity and specificity for colour and greyscale HDR images.

The findings of this study have a number of implications for research to develop novel robust techniques for the analysis of EEG to increase the contributions EEG makes to the diagnosis of CVD condition. In future work, we will develop a commercially exploitable technology to diagnose children suffering from Colour Vision Deficiency based on EEG and HDR images.

Chapter 7 Enhancement of the quality of dental X-ray images to reduce patient radiation exposure and improve diagnoses: A pilot study

7.1 Introduction

The use of X-rays is an integral part of clinical dentistry. Radiographic examinations is an irreplaceable special investigation tool that is necessary in the majority of patients. A wide range of intra- and extra-oral radiographic techniques are used for diagnosis of oral diseases, treatment planning and for monitoring treatment outcomes [31] [48]. X-ray exposure involves a risk to the patient. It is essential that any x-ray examination should show a potential net benefit to the patient, weighing the total diagnostic benefits it produces against the detriment the exposure might cause. A useful diagnostic investigation is one that the results of it will alter or add confidence to a clinician's diagnosis or treatment planning [31], [188], [189].

There is also a need to ensure that the radiographic information contributes to achieving optimal standards of diagnosis and patient care and that clinically significant diseases are not missed. This may mean that some operators will have to take more radiographic examinations due to the poor quality of initial radiographs. Particular problems during radiographic examinations are patients with special needs, paediatric patients, gagging, localised anatomical challenges etc.

One of the most important protocols in a dental surgery is a quality-assurance programme (QA). QA is a plan of action, concern and responsibility to ensure that the x-ray images obtained in a dental practice are of the highest standard, with minimal exposure to the patients and dental staff and resulting in the maximum diagnostic yield. An effective QA policy that monitors the use of radiation and the quality of x-ray images in a dental surgery is a shared responsibility of all members of the dental team[31] [48].

Clinical audit is a statutory requirement as well as a useful tool to help clinicians improve their practice or to check if the all members of the dental team meet expected radiographic standards. The National Radiological Protection Board guidance describes three grades of radiograph quality based on the clinical value of the image, Table 7-1 [188].

Table 7-1: Subjective quality rating of radiographs (based on NRPB 2001 guidelines)

Rating	Quality	Basis
1	Excellent	No errors of patient preparation, exposure, positioning, processing or film handling.
2	Diagnostically acceptable	Some errors of patient preparation, exposure, positioning, processing or film handling, but which do not detract from the diagnostic utility of the radiograph.
3	Unacceptable	Errors of patient preparation, exposure, positioning, processing or film handling, which render the radiograph diagnostically unacceptable.

Table 7-2: Recommended minimum targets for quality (based on NRPB 2001 guidelines)

Rating	Quality	Percentage of radiographs taken
1	Excellent	Not less than 70%
2	Diagnostically acceptable	Not greater than 20%
3	Unacceptable	Not greater than 10%

On the basis of this grading, Table 7-2, not less than 70% of all radiographs taken in a dental surgery should be of grade I, not greater than 20% of grade II and not greater than 10% of grade III. Improving the quality of dental x-ray images, without re-exposing patients to ionising radiation, would enhance the diagnostic power of radiographs and improve patient care[48], [31].

HDR imaging is an important new development which may be used to enhance image quality and reduce the number of unacceptable radiographic images. HDR provides the ability to capture a wide range of luminance values, similar to that of the human visual system, and this has led to its widespread application in many areas including home entertainment, medicine, scientific imaging, computer graphics and multimedia communications[33], [34], [32].

Previous studies [11], [20] have suggested different multiscale methods for x-ray enhancement, such as a wavelet transform and Laplacian pyramid transforms. Slavkovic-Ilic et.al [190] described the possible use of HDR imaging for LDR echocardiograms enhancement. Kanelovitch et.al.[191] addressed the issue of companding HDR mammograms to LDR mammograms, by enhancing the diagnosis in both types of abnormalities. Trpovski et al. [32] used HDR processing to enhance the legibility of dental radiographic images to minimise exposure to radiation. However, their approach involves the use of two poor quality radiographs from the same subjects because of the requirements of HDR processing. We hypothesise; only one poor quality radiograph may be used to keep exposure to radiation to a minimum. For clinical acceptance, there is also a need to automate the image quality enhancement process, with minimal user intervention, to make it easier for the busy clinician. Our study aims to explore the use of HDR image enhancement techniques on the routinely collected radiographic images to answer the following research questions:

- Can HDR techniques be used to enhance the quality of poor dental images and make them acceptable for clinical use to eliminate the need for additional patient exposure to radiation?
- By using only one poor quality dental image, can we generate an HDR image, without the need at least two overexposed and underexposed image of the same scene.

7.2 Tone mapping operators

TMO processing must be modified, in order to gain the HDR image, and is not directly obtained from the radiographs. We have carried out a number of experiments [11], [35] and determined the best TMOs that can be applied to greyscale the HDR images. The procedure consisted of the following steps:

- Generating the HDR image from one poor quality radiographs image.
- Tone mapping and gamma correcting value were also calculated during this procedure.
- Displaying the image on the LDR display.
- Seven, fully blinded, dental professionals being asked to grade the original and modified images.

In this experiment, we tried to obtain the best possible image from only one low quality radiograph. One of the methods for capturing an HDR image is combining multiple single-exposure LDR images of the same scene. Since we had only one image per scene, an original image, we generated simulated over- and underexposed images by subtracting and adding the value of 0.2 respectively, from pixel intensities of the original image (assuming a normalized scale: 0-black to 1-white). The best three TMOs from previous studies that work efficiently with greyscale HDR images were used: Reinhard algorithm, Durand algorithm, and Drago algorithm, AL1, AL2 and AL3 respectively, which all are global TMOs (see Table 2-1).

7.3 Materials and methods

7.3.1 Ethics

Ethical approval from the NHS, Health Research Authority, NRES Committee South West Cornwall and Plymouth University approved this study.

7.3.2 Data collection

Ten radiographs of Grades 2 and 3 (the grade given due to the quality of the image and not due to a technical issue) were randomly selected from the SoelHealth database. Patients’ details are not recorded on radiographs. The HDR images were processed by three TMOs plus the original image, giving 40 processed radiographic images. The images were then stored in a database accessible from a website. Seven, fully blinded, dental professionals from the University of Plymouth, Peninsula Dental School, UK, were asked to grade the original and modified images.

Original images	Reinhard	Durand	Drago

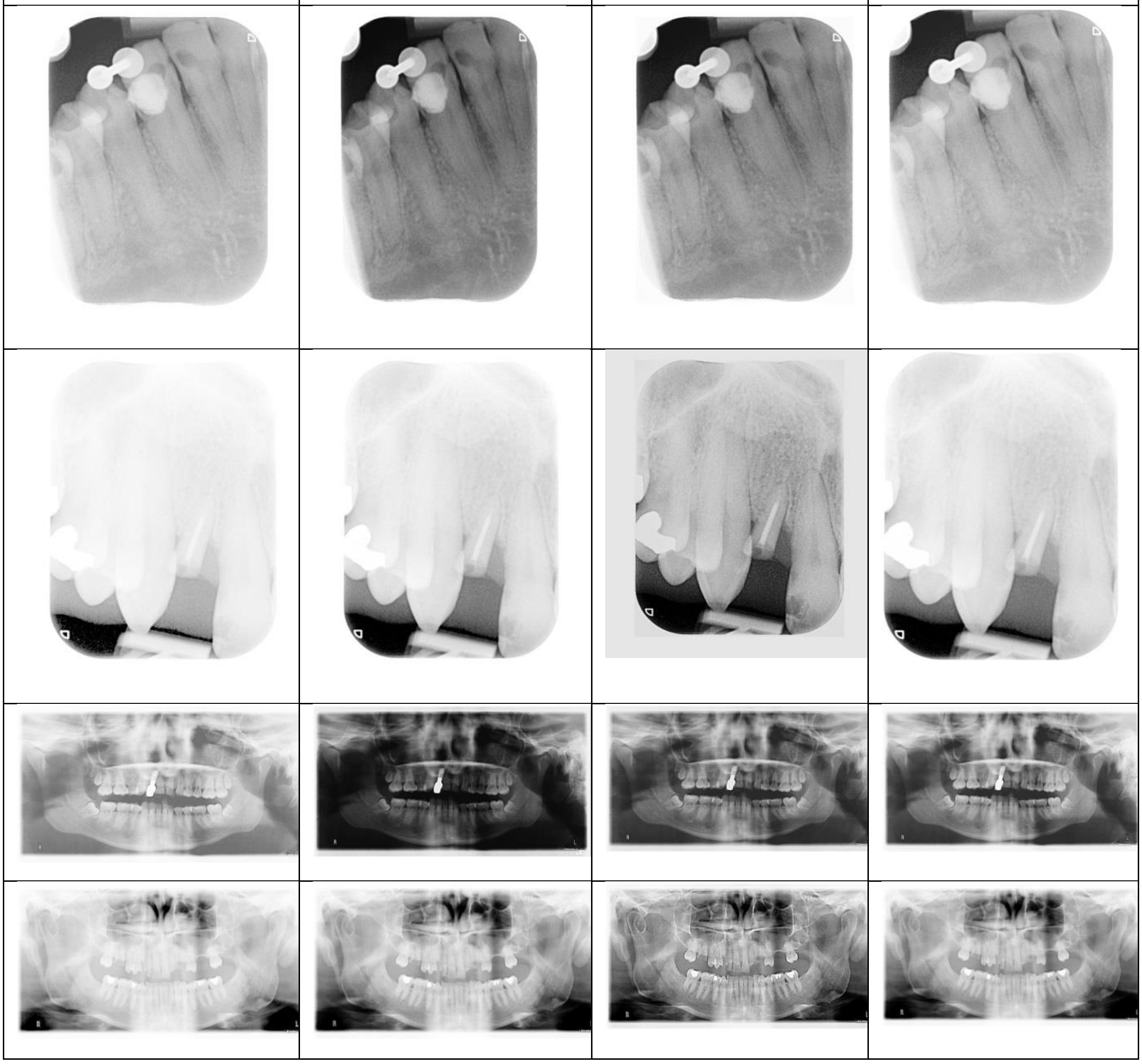

Figure 7-1: Example on the orginal and processed HDR images

7.3.3 Acquiring test images

For the generation of tone-mapped images, see Figure 7-1, we used the HDR Toolbox [3]. Slight modifications were made to the HDR generation algorithm, mainly because of the greyscale nature of the images and the fact that there were no real photometric exposure values that can be used with the algorithm. For HDR generation, I've modified the algorithm to work in one plane, instead of working on all tree RGB planes, because it performs the same calculation for every colour plane. The same was done for tone mapping operators, if the operator modifies all colour planes in the same way - we just simplified it to use only the luminance.

7.4 Results

Figure 7-2, shows the average grading values for the original and the processed HDR images for the three TMOs, for 10 radiographies x-ray images, graded by seven, fully blinded, dental professionals with 95% confidence interval (CI). Most of the grading of the original images were grade 3, fewer were grade 2. From the results, we can see that the Reinhard algorithm (AL1), Durand algorithm (AL2), and Drago algorithm (AL3), all provided a very good result as judged by the radiologist, especially, Durand algorithm (AL2).

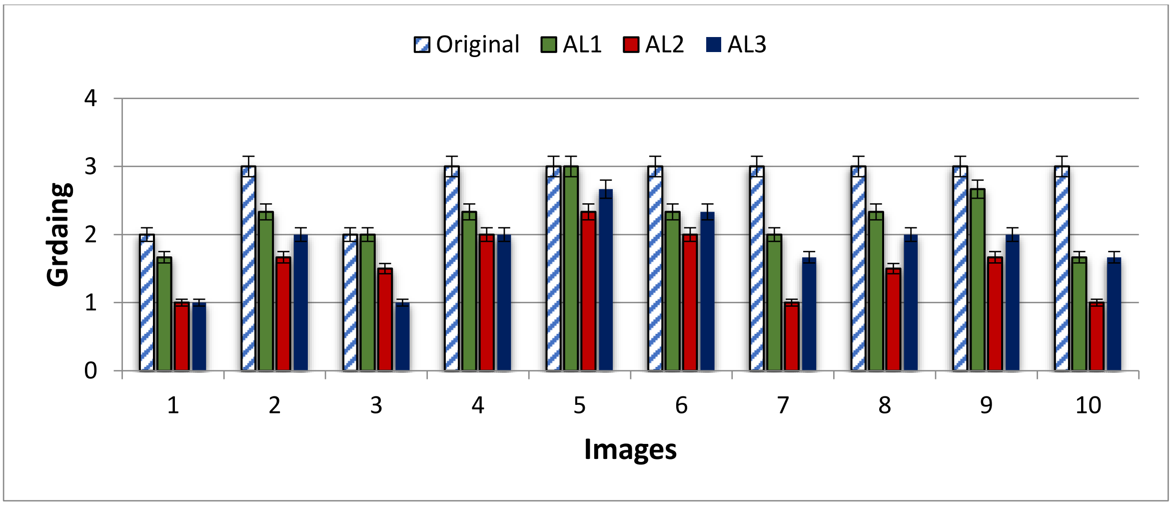

Figure 7-2:The average of the dentists grading for the original and processed HDR images.

7.5 Discussion

Medical images are an important part of the diagnostic process. In many cases, the accuracy of diagnosis depends on the quality of the image. The investigation and development of new medical image processing methods and systems has received great attention over the last two decades. This is due to its wide range of applications in computer assisted methods and computer-aided methods.

The proposed study presents a new image enhancement method for X-ray images. The method uses an HDR-image creation as a technique to increase the image dynamic range, by generating the HDR image from one poor quality radiograph image. This allows after mapping an HDR-image to an LDR-image (low dynamic range image) to get a better distribution of the intensity over all pixels in the image. The result is enhanced brightness, contrast and/or sharpness which, in our study, led to enhancing the grading level from 3 to 2 or even 1, moreover from grade 2 to grade 1.

Reinhard algorithm (AL1), Durand algorithm (AL2), and Drago algorithm (AL3), all provided very good results as judged by the radiologist, especially, Durand algorithm (AL2). In our study, we have restricted the HDR processing to global tone mapping algorithms based on the literature and our previous study. Local image adjustments could result in visually nice, but medically inaccurate radiographs. This will lead to improving the quality of dental x-ray images, without re-exposing patients to ionising radiation; this would enhance the diagnostic power of radiographs and improve patient care.

7.6 Summary

The study may provide an objective means of reducing the proportion of poor quality radiographic images and hence the risk of patient repeated exposure to radiation by using HDR techniques. HDR image processing techniques used for photography are shown to be useful for the images obtained with non-visible radiation. Significant radiograph legibility enhancement is achieved. Very good results were obtained in the experiment where we have two images taken with different brightness. We obtained a high quality image that is comparable, in some cases even better than the reference image. For medical purposes, only experiments giving "photo-realistic" effect were acceptable. There is a huge variety of cases where some parts of the image can be enhanced using tone mapping operators, but the purpose of the radiography is not to get a beautiful image. The image must be legible and suitable for gathering accurate medical information. A software toolkit can be created that enables the radiologist to manually modify selected parts of the image and enhance them in various ways getting a clearer and better view of the details, and enabling him to perform reliable diagnostics. After the HDR image processing of one low quality images, we get a radiograph that has much more information embedded in it than the original image. We get a real HDR image with considerably more luminance levels. There is a rising volume of software, which tries to automatically recognize and pinpoint the key elements of the radiograph.

The main limitation is that the grading of radiological images is subjective. Thus, the outcome of the study and its widespread acceptance will depend to an extent on the experience and expertise of the dentist and therapists involved in the study. However, with careful selection these limitations should be minimised.

This research is a preliminary work to demonstrate proof of concept. We only have initial results. Although there is no clinical validation yet the initial results are promising. In future, we plan to develop a machine learning model to predict the grades of the images. This will involve the extraction of the salient features from raw grades 1, 2 and 3 images and to use these to train a machine learning to predict the grades of images. The study will employ machine learning techniques to learn the profile of the images in each grade in the “Training Set” and then test its accuracy and predictive values in the “Test Dataset”.

Chapter 8 Review, Future Work and Conclusions

8.1 Introduction

High dynamic range images represent a much greater range of colour and brightness levels than those offered by existing, standard, or low dynamic range images. HDR images greatly improve the overall quality of experience of visual content, making it appear much more realistic and appealing to the consumer. HDR is one of the key technologies of a future-imaging pipeline, which will change the way digital visual content is represented and manipulated.

Real-world scenes are not only brighter and more colourful than their digital reproductions, they also contain much higher contrast. Traditional imaging, unlike HDR, is not able to represent such high-contrast scenes. To faithfully represent, store, and reproduce all these effects, the original scene must be stored and treated using high fidelity HDR techniques.

Tone-mapping operators provide a useful means of converting a high dynamic range image to a low dynamic range image to achieve better visualisation on standard displays. Although mobile devices are becoming popular, the techniques used to display the content of HDR images on the screens of such devices are still in their early stages of development. Thus, while several studies have evaluated TMOs on conventional displays, few have evaluated TMOs on small screen displays such as those used in mobile devices.

Traditionally, evaluation of the perceived quality of multimedia content is conducted using subjective opinion tests such as MOS. However, it is difficult for the user to link the quality they experience to the quality scale. Moreover, MOS does not give an insight into how the user really feels at a physiological level in response to satisfaction or dissatisfaction with the perceived quality [3]. To address this issue, measures that can be taken directly (implicitly) from the participant have attracted considerable interest. The electroencephalogram is a promising approach that can be used to assess quality related processes implicitly [2]. At present, there is no standard use of electrophysiology to assess QoE, although contributions are being made to the ITU-T regarding the use of physiological measures for QoE (e.g. ITU-T Contribution COM 12-(039, 112, 103, and 202). However, implicit QoE approaches are still in their initial stages of development and further research is needed to understand the nature of the neural signals recorded and their associations with user-perceived quality in terms of QoE [5].

8.2 Contribution to Knowledge

The aim of our project was to investigate the quality of experience of high dynamic range images using the EEG and assess the potential applications this may have in healthcare. To achieve this goal, a critical review of relevant literature on HDR methods, techniques and applications was first conducted to obtain knowledge and insight into key HDR imaging issues. Additionally, relevant available resources (e.g. data and software tools) were identified and case scenarios were used to help develop the algorithms.

Second, a test facility for studying HDR was set-up. This included a development and test platform for HDR investigation (including algorithm development, testing, and evaluation in different scenarios). The platform included available open source resources (e.g. data and software tools) and facilitated the execution and testing of key operations in HDR imaging workflow and pipeline.

Third, subjective and objective methods were used to evaluate the most popular tone-mapping operators. Different mobile displays and resolutions were used under normal viewing conditions for the end-user using the LDR display as a reference. Preliminary results show that, compared to computer displays, SSDs have an impact on the performance of TMOs. The results will be presented in a conference paper, which has been accepted for presentation at ICC 2016.

Fourth, the first experimental framework was repeated using tone mapping performances for greyscale HDR images. In this experiment, we investigated and compared the impact of TMOs for traditional displays and SSDs with different devices and resolutions on Quality of Experience (QoE). A second grey image dataset was thus added to the coloured HDR images. This involved converting the images in the first dataset to greyscale images using MATLAB implementations of Exposure Fusion. The results were reported in a paper submitted to the IET journal.

Fifth, we investigated the relationships between changes in EEG features and subjective quality test scores (i.e. MOS) for HDR images viewed with a mobile device. The results show that changes in the gamma and beta bands correlated negatively with MOS, whereas positive correlations were observed in the alpha band. Coupling between activities in the delta and beta bands, (i.e. a positive correlation between power in the fast beta and slow delta frequency bands) was related to anxiety and dissatisfaction. Thus, increases in the degree of coupling are associated with decreases in HDR quality. This also suggests that human emotions play a significant role in the QoE assessment of HDR images. These findings will potentially enable us to develop an objective QoE perception model and were presented in a conference paper for the ICM 2017.

Sixth, our model is based on existing research conducted on HDR image QoE assessment; which suggests that coupling between delta and beta frequency bands can be used to characterise human emotions such as anxiety and dissatisfaction. Research aimed at establishing models to predict user's acceptance of mobile images has thus far been limited. Our proposed model can predict user acceptability and satisfaction for various mobile HDR image scenarios based on delta-beta coupling.

HDR image quality was predicted in terms of the MOS. Subjective quality tests were conducted to develop and evaluate the model. The model exhibited good prediction accuracy of at least 82%. The results are contained in in a journal paper in preparation.

Seventh, when HDR images are viewed and participants with CVD assess image quality, this may cause changes in the EEG that are associated with CVD. Such changes can be accentuated when viewing HDR images. HDR imaging is used in numerous applications to create visually pleasing images, especially scenes that contain very bright, direct sunlight to extreme shade or very faint shades, such as indoor areas and outdoor scenes. In this study, we proposed a new method to detect CVD from EEG and HDR images. We invoked changes in the brain activity due to CVD by showing HDR images to participants. The results will be reported in a paper to be submitted to the IEEE transaction on Multimedia.

Finally, a method was developed to process dental radiographs (x-rays) of poor legibility using several HDR algorithms to generate radiographs of acceptable quality (good legibility). Due to the nature of the radiographic images, which is significantly different from classical digital images, slightly modified image processing techniques were applied. The main result is an algorithm for acquiring and processing a set of images to minimise the amount of radiation applied to the patient. The Radiograph's grading after HDR processing was significantly improved.

8.3 Limitations of the current work and discussions

There are a number of limitations in the project and programme of work reported in the thesis. These include the following:

a) **Experimental set-up:** While our current experimental setup provides new and relevant information, there are also several limitations and challenges in our method that need to be addressed.

(1) TMOs and HDRs: the TMOs arising in our HDR stimulus do not cover the full range of possible qualities as these were only were ten of the most well-known TMOs. Thus, several experiments must be conducted to examine different combinations of TMO qualities.

(2) Dataset: the relatively small size of the dataset meant that it was limited to natural scenes; this should be expanded to cover other types of content.

In particular, the dataset for the CVD is only 20 subjects; the number should be increased to 50 inorder to evaluate this model sufficiently. Moreover, giving the need to detect CVD early, it will be desirable to collect data from children.

(3) Displays: HDR images still need to be presented on HDR displays. They cannot be displayed easily on the current SSD or LCD monitors as these have dynamic range limitations of about 100:1, which is very low compared to HDR displays.

b) **Limitations using mobile devices:** The main limitations encountered when using mobile devices in our experiments are listed below:

(1) Mobile devices usually have limited memory available for running applications. Moreover, they must run several applications in parallel, which further decreases the memory available for imaging applications.

(2) Computational power is also limited which has a twofold impact on the implementation of an HDR system. Firstly, the fusing process must be implemented through simple arithmetic operations to keep the processing time as short as possible. Secondly, the number of captured images must also be limited.

(3) Another limitation of mobile devices is the lack of support they provide for floating point operations. This complicates the implementation of multi-frame approaches that transform the input images in the radiance map (radiance map computation usually results in floating point variables).

(4) A notable limitation of the SSD is that the original resolution and aspect ratio of the images were maintained so that a straight comparison could be made between the reference and the tone-mapped sequence of the mobile device. This guarantees that no information was lost when the content was converted to a lower resolution. Small screen sizes would have required the content to be retargeted. Additionally, participants were not allowed to adjust the brightness of the SDD

c) **Limitations using the EEG device.** The main limitations we encountered when using an EEG device are listed below:

(1) We used a portable 2-channel EEG device for multimedia quality assessment which was suitable for the lab environment. The 2-channel EEG is a consumer-grade EEG device that is low-cost, lightweight, and inexpensive. However, such devices were not originally intended for research, although they are becoming increasingly popular due to their flexibility and the wide range of suites they offer.

(2) Physiological differences between individuals when using the EEG may generate systematic errors between participants or groups. Another key challenge is to therefore design QoE assessment so that it is applicable to a general population.

(3) Attaching sensors to participants can cause a certain degree of discomfort or result in them changing their natural behaviour. Moreover, experiments requiring attached sensors are often considerably more complex. Such factors can have a direct impact on the duration of the experiment and, consequently, on the availability of participants.

(d) Limitations in the dental images: For X-ray images, the main limitation is that the grading of radiological images is subjective. Thus, the outcome of the study and its widespread acceptance will depend to an extent on the experience and expertise of the dentist and therapists involved. However, with careful selection these limitations should be minimised.

8.4 Suggestions for future work

There are four main aspects of the research that can be improved and extended in future work.

1. The dataset in the studies should be increased to have enough data to develop, test and validate the results.
2. There is a need to recreate the conditions under which mobile devices are used by considering the impact of different viewing angles and distances. This should help determine the effect the viewing conditions have on the QoE of the HDR image.
3. For X-ray radiographic images**,** a machine learning model needs to be developed to predict the grades applied. This will involve extracting salient features from raw images of grades 1, 2 and 3 and then using these to train a machine to predict the grades of images. Thus, after enhancement of a grade 3 image, we could run it through the machine learning model to predict the grade of the enhanced image. This can then be compared with human grading. We will randomly split "cases" for each grade into two groups ("Training Dataset" and "Test Dataset"). Machine learning techniques will be employed to learn the profile of the images in each grade in the "Training Set" and then the accuracy and predictive values of these techniques will be tested in the "Test Dataset". State of the art learning algorithms such as Support Vector Machines (SVM), random forest, and Neural Networks (NN) will be used as representations of the complex models hidden in the data.

4. A demonstrator should be developed to detect CVD in children.
   This will involve overcoming a number of challenges:
   First, I will need to collect EEG data from children with and without CVD, and

extract robust EEG-based biomarkers for the condition. This will require ethics approval for the data to be collected.

The accuracy of the demonstrator depends to a large extent on the accuracy of the models we will develop to diagnose CVD. Ideally, we would need a large dataset of EEG signals recorded from a large number of children. To overcome this problem, we will use intelligent data analysis techniques and advanced machine learning techniques when constructing models. This will allow us to develop accurate models from a limited number of EEG signals.

Another challenge involves validating the demonstrator to ensure its acceptability. To address this, we will recruit more participants so that some of the data can be used for validation purposes. The performance of the demonstrator should be compared with existing methods. .

8.5 Conclusions

Motivated by the exponential growth of HDR images that can capture a wide range of luminance values, analogous to that of the HVS, thisthesis assessed the quality of experience of HDR using the EEG and investigated two potential applications in healthcare.

The initial stage of this project simulated existing TMOs in colour and greyscale HDR images and evaluated their QoE performance using SSDs. The device size and resolution of TMOs affect QoE for colour and grey HDR-image in the same way. Shannon Entropy is a strong objective measure for colour and grey HDR images, suggesting that entropy can be used in an automated HDR quality-control-assessment-scheme.

We then proposed a novel electrophysiology-based QoE assessment of HDR image quality that can be used to predict perceived image quality. Moreover, the correlation between the mean power in the delta and beta bands is a measure of coupling between the activities in these bands. This is linked to negative behavioural characteristics (e.g. anxiety, frustration, dissatisfaction).

Based on previous findings, we proposed a model that can predict user acceptability and satisfaction in various mobile HDR image scenarios based on delta-beta coupling. HDR image quality was predicted in terms of the MOS. The performance of the model was evaluated and yielded a good prediction accuracy of at least 82%.

We developed a new method to detect CVD using EEG and HDR images. Power in the bands and their ratios were used as candidate features for the development of a model to diagnose CDV with high sensitivity and specificity. We used machine learning techniques to select several features (power in the bands) whose combined diagnostic value in the detection of CVD is high. Machine learning techniques were used to classify CVD in participants with the condition and distinguish them from those without. The performance of the model (> 90% sensitivity and specificity) therefore suggests that an analysis of the EEG power spectrum may provide an accurate and reliable method of detecting CVD.

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