2020-05

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10.1109/wccct49810.2020.9170009
2020 World Conference on Computing and Communication Technologies (WCCCT)
IEEE

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***Abstract*—In the present paper we give a classification of the position and the number of inertial measurement units (IMU) used to detect human activities and position tracking based on literature review. It presents a separate view of IMU position and IMU numbers placed on the human body. In total 60 relevant studies were found which focused on human activity recognition (HAR) and tracking with dead-reckoning. The focus lies on the number, the sample frequencies and the positioning of IMUs. To the best of our knowledge, this is the first work which looks particularly at the number and position of IMUs. The result shows that a comparison between the different studies fails, because the description of the positions is not precise enough and not uniform.**

Keywords-inertial measurement unit (IMU); human activity recognition (HAR); position tracking; motion detection; personal dead-reckoning (PDR); inertial sensors

I. Introduction

In human activity recognition (HAR) and tracking the usage of inertial measurement units (IMU) is quite common. There is a countless quantity of possible combinations and placements of the IMU(s) on the human body. Additionally a vast number of models and their intermixture can be chosen. This makes it quite complicated to choose an appropriate design. The experience gained from previous researches can help to decide for a suitable solution. The current paper addresses the challenge by providing a large summary of previous studies. The focus lies on the used IMU positions on the human body. This is one of the first challenges for researchers in the fields of HAR and human tracking. In this work the focus is not on methods and models or the combination of all three. In the best of our knowledge, the placement and number of used IMUs has not previously been reviewed exclusively. The paper is structured as follows. In the introductory section we give a short overview of IMU, dead reckoning and HAR. Section II discusses the related work. Section III shows the results which are summarised in table I. Section IV concludes the paper.

A. Inertial Measurement Unit

An IMU typically consists of three different sensor types. First the inertial sensors are accelerometers and gyroscopes. Secondly sensors for velocity measurement are odometer, step detection and doppler. The third group are sensors for attitude measurement, these are magnetometer, gyrocompass and trajectory. The design of a strapdown-IMU has gained importance due to its small size and low production costs [1]. It is based on micro-electro-mechanical system (MEMS) semiconductor sensors and signal processing with long-term stability [2].

B. Dead Reckoning

Tracking systems based on dead reckoning operate completely autonomous. No existing infrastructure or training data is required. They measure the change of position with so-called IMU(s) but need a known start point. Then they calculate the current position based on the measurements. The current position replaces iteratively the known start position for the next calculation of a current position. This means the previous position is used to obtain the next position. This iteration is important for the accuracy of the tracking solution [2]. Additional information like human activities are often involved to determine the position more precisely. Strozzi et al. [3] show that position of the sensors is important for tracking systems. A placement near the centre of mass, the lower back, brings better results in determining the orientation, whereas the step length can be measured more accurately on the foot.

C. Human Activity Recognition

HAR is a broad research field. There are solutions available based on sensors, radio frequency and visual technologies. In principle, human activities can be identified in three ways: by external sensing, wearable sensing or hybrid. The degree of monitoring which is required to identify the activities is divided into semi-supervised or supervised [4]. Different attributes and sensors can be used for HAR. This includes

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environmental attributes, acceleration, location and physiological signals. The accelerometer is the most used sensor to recognise ambulation activities. The obtained accuracy of it for the motion of walking and running can be quite high: 92.25% [5], 95% [6], 97% [7] or 98% [8]. The position and quantity of the used sensors attached to the human body are important for the HAR. Cleland et al. [9] found out that extending from one to two sensors enhanced the proper classification of the activities.

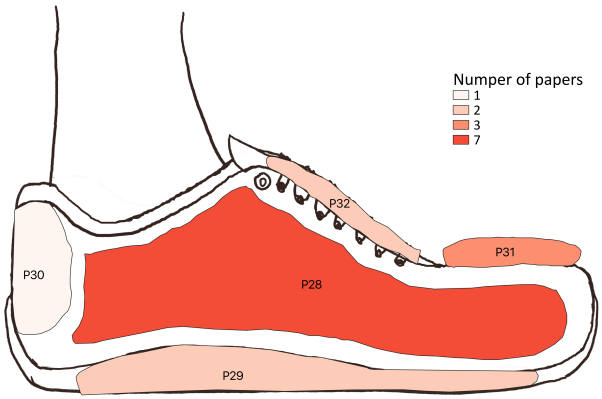

Figure 1. The different IMU positions at the shoe or foot. While some positions can be clearly assigned to the shoe this is not possible with others. These were grouped in P28. Generally it is not distinguished between left and right.

II. Related Work

Lara et al. [4] compared in their survey 24 papers and is highly detailed and wide-ranging. They give an overview of the used features, the accuracy of the solutions, the energy requirements and the machine learning (ML) techniques. A state-of-the-art overview about used classification algorithms for HAR systems is shown in the work of Ramamurthy et al. [10]. They additionally offer a good overview regarding machine learning in HAR. Bao and Intille [11] summarise several papers in the field of activity recognition. The overview also shows the number of sensors and their position on the human body. In addition, the accuracy of the different solutions and the activities are listed. However, their focus was only on the acceleration sensors. Atallah et al. [12] compared 14 recent approaches of using accelerometers and listed the corresponding sensor positions. An overview of the human activities, the number of IMUs used and their data acquisition frequency is not included. Attal et al. [13] reviewed 18 studies on accelerometer placement for HAR. In addition to the position of the sensors and the recorded activities, the average accuracy of the classification is also recorded. Cleland et al. [9] investigated extensively the optimal position of the accelerometer with regard to the recognition of everyday activities. They compare 15 studies by comparing human activities, the position of the accelerometers and the accuracy including the algorithms. All found surveys contain comparisons with different foci.

III. Results

The section of the results is divided as follows. The first part consists of a table with an overview of all found relevant research focusing on IMUs in HAR and human tracking. The second part includes a presentation of the quantitative results from the findings in table I. The third part shows the qualitative results extracted from the discoveries in table I.

A. Overview of Found Research

In total, 60 relevant studies were found. From these researches the different categories hybrid, number of IMUs, position of IMUs, human activities, axes of used sensors and sampling frequencies were extracted. This procedure resulted in the findings shown in table I. In order to get a better comparability between the different studies, table II classifies the results of table I. Likewise, our examination of the papers shows that same positions are named differently. In order to be able to classify them nevertheless, the acronyms are filtered out and classified on the basis of text and image inspection. To do this, we defined the following special cases. Whenever the paper described to fix the IMU(s) on the dominant side, it was classified as right side. If no side is indicated or visible, the IMU was not been taken into account. The same applies to IMU(s) which are mounted to clothing bags like first chest pocket and pocket of trouser. Afterwards, the findings are graphically mapped to the human body in figure 1 and figure 2. They separate the number of IMUs and the position of IMUs.

B. Quantitative Results

The survey revealed that 42 studies focused on using IMUs stand alone. Just the minority of 18 researches used an hybrid system and took into account other types of sensors like a barometer. The amount of utilized IMUs ranges from 1 to 13 devices. The overall mean is the usage of three IMUs, whereas within 28 studies the most researchers made just use of one IMU. These researches mainly focused on normal activities of daily living and the transitions between these activities [14]–[16]. The maximum of 13 IMUs was just related to one research which surveyed the complex activity alpine skiing [17]. The used number of axes of the IMUs is in the range of 2-axis IMUs to 9-axis IMUs with a mean of 6-axis IMUs. The 3-axis IMU was the most popular IMU as 20 researches used one or more of it. The applied sampling frequency ranges from 1 Hz to 512 Hz. The overall average is 76.62 Hz, whereby 50 Hz was with 13 studies most often used. The maximum sampling frequency was found in a work which investigated human tracking [67]. On the other side, the minimum sampling frequency was found in a study focusing on activities of daily living [19]. Some studies focused on finer grained household activities [19], [20]. In addition, some other studies concentrated on special topics like position estimation [3], [21], alpine skiing [17] and doing sport [18]. Possible placements of the IMUs include more or less all extremities

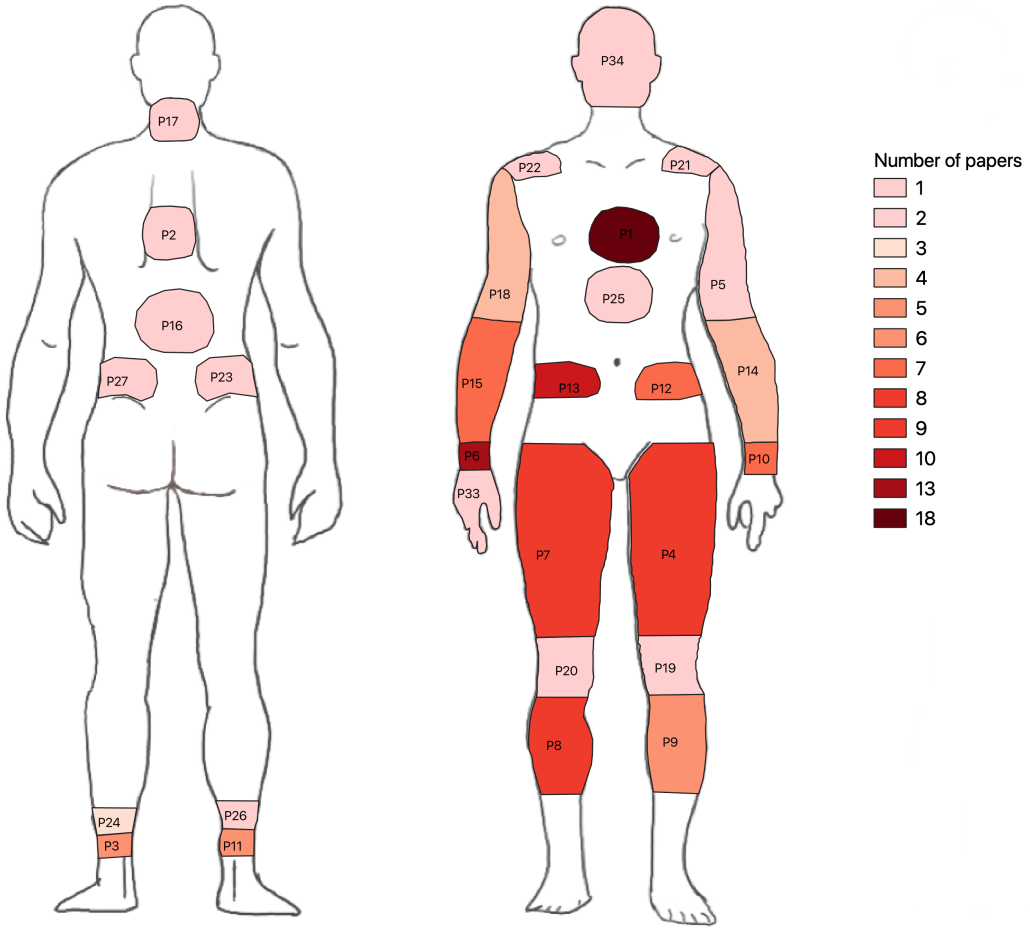

Figure 2. The different positions of IMUs at the human body. The different colours represents how often a position was used in the papers. The labels links to the extracted positions in table II where the description and naming can also be found. Position which could not be classified are excluded from the figure. This applies to IMUs attached at clothes as well as those where it is not clear whether it is the right or the left side. The positions on the shoe and on the foot are not considered in this figure and can be seen in figure 1.

on the human body.

Table II shows that in total 34 different positions are identified. The most common position is chest. It is used in 18 papers. Most acronyms are used for the foot followed by the chest and waist. These results can also be seen in figure 1 and figure 2.

C. Qualitative Results

One interesting result was the elimination of the drift of the IMU (accelerometers) [14] by using the technique zero velocity update (ZUPT) during the step phase in which the boot is on the ground. Several studies concluded that the appropriate placement of the IMUs is dependent upon the activities which have to be classified [12], [22], [23]. For instance, [22] stated that positioning the IMU at the ankle can fail in differentiating certain movements in the upper-body. Therefore, in a real application scenario it is important to choose the positions of the IMUs according to the activities which should be detected. Even though the amount of IMUs used dependent on the type of activities certain researches concluded that reducing the number of IMUs does not always come with a substantial loss in the quality of the data. For example, [19], [24] came to the result that using two IMUs, one at the thigh and one at the hand or wrist, can help to appropriately identify activities of daily living. Moreover, [9] observed an improvement of using two IMUs in comparison with using just one IMU. However, additional IMUs did not end up in a further significant difference in accuracy. [23] concluded a general improvement in performance when using a combination of multiple IMUs.

The position description of the foot is particularly striking. Here, the accuracy of the position information is often based on the to abstract term foot or shoe. With regards to the qualitative best position or combination, the comparability is not given.

TABLE I. Listing of used IMUs in respect to HAR and IMU placement

Ref.	hybrid (y/n)	IMUs	Position	Human Activities	Axes	Hz
[25]	no	1	waist	position estimation, standing, walking, walking upstairs, walking downstairs	9	50
[26]	no	2	waist, thigh	sitting, standing, lying, moving	2	50
[27]	yes	1	chest	sitting, running, walking	3	50
[28]	no	1	waist	upright standing, sitting down, moving trunk and arms, picking up objects, climbing wall bars, jumping, walking, running, resting lying down, moving lying down	3	50
[29]	no	1	back	standing up, sitting down, lying down, walking, walking upstairs, walking downstairs, running	3	32
[30]	yes	2	both feet	position estimation	6	
[31]	no	6	left wrist, belt, necklace, in the right trouser pocket, shirt pocket, and bag	sitting, standing, walking, walking upstairs, walking downstairs	2	50
[32]	no	1	hand	standing, walking, running, climbing up stairs, climbing down stairs, sit-ups, vacuuming, brushing teeth	3	50
[33]	no	1		walking, walking upstairs, walking downstairs, standing-up, sitting-down, falling	3	
[11]	no	5	4 limb positions (right ankle, left upper leg, left upper arm, right wrist) and hip	walking, sitting and relaxing, standing still, watching TV, running, tretching, scrubbing, folding laundry, brushing teeth, riding elevator, walking carrying items, working on computer, eating or drinking, reading, bicycling, strength-training, vacuuming, lying down and relaxing, climbing stairs, riding escalator	2	76
[34]	no	4	both wrist, left ankle, chest	lying, sitting, standing, walking, running, cycling	9	50
[35]	no	3	trunk, both thighs	lying, sitting, standing, walking speed	2	25
[36]	yes	1	is not explicitly mentioned	localisation, walking	9	100
[37]	yes	1	trouser pocket, hand	sitting, standing, lying, walking, walking upstairs, walking downstairs, cycling, dancing (style 1-3), talking on phone, typing text message, sitting in bus, standing in bus	6	100
[38]	yes	7	both feet, both lower legs, both upper legs and the pelvis	position estimation	9	30
[39]	no	7	waist, right wrist, left wrist, right arm, left thigh, right ankle, left ankle	stand to sit, sit to stand, sit to lie, lie to sit, bend to grasp,rising from bending, kneeling right, rising from kneeling, look back, return from look back, turn clockwise, step forward, step backward, jumping	5	
[40]	no	1	waist	sit-to-stand transition, stand-to-sit transition, walking	3	45
[41]	no	1	wrist	brushing teeth, hitting, knocking, working at a pc, running, walking, swinging	3	100
[22]	no	5	two on the wrist, one on the waist, and two on the ankles	stand, sit, lie down, walk forward, walk left-circle, walk right-circle, turn left, turn right, walking upstairs, walking downstairs, jogging, jump, push wheelchair	5	30
[42]	no	1	first chest pocket, then left waist, then right waist	tilt up, standing, sitting down, liying down, fall down, walk around, running	3	10
[18]	no	5	both lower legs, both lower arms, pelvis	gait, sport, daily live	6	240
[43]	no	3	right wrist, left hip, chest	sitting down, running, squat, walking, standing, crawl, lay down (on the chest) and hand movements (while standing)	3	50
[44]	no	1	right front hip	walking forward, walking left, walking right, walking upstairs, walking downstairs, jump up, runing, standing, sitting	6	100
[16]	no	1	waist	Sit-to-stand, stand-to-sit, lying, lying-to-sit, sit-to-lying, walking(slow), walking (normal), walking (fast), fall (active), fall (inactive), fall (chair), circuit	3	100
[45]	no	3	lower leg, upper leg, chest	tracking	9	50
[15]	no	1	waist	walking, walking upstairs, walking downstairs, riding escalator	9	50
[46]	no	3	lower dominant arm, chest, foot	lying, sitting, standing, normal walking, nordic walking, running, cycling, other	9	100
[14]	no	1	users boot	fast walking, slow walking, walking upstairs, walking downstairs, slopes	6	
[9]	no	6	chest, wrist, lower back, hip, thigh and foot	walking, running on a motorized treadmill, sitting, lying, standing, walking upstairs, walking downstairs	3	51
[21]	yes	1	foot	position estimation	6	100
[13]	no	3	chest, right thigh, left ankle	standing, stair descent, sitting, sitting down, sitting on the ground, from sitting to sitting on the ground, from lying to sitting on the ground, lying down, lying, walking, stair ascent and standing up	9	25

[47]	no	7	both feet, both lower legs, both upper legs, waist	walking, running, jumping	9	60
[48]	yes	5	lower leg, upper leg, lower arm, upper arm, pelvis	lying down, standing, sitting, walking, running, walking upstairs, walking downstairs, cycling, rowing, carry weight, move weight, bicep curls, jumping jacks, push ups, sit ups	3	30
[19]	no	3	wrist, hip, thigh	preparing for work, going shopping, doing housework, brushing teeth, taking a shower, sitting, driving car, eating at table, using the toilet, sleeping, walking, working at computer, waiting in line in a shop, strolling through a shop, hoovering, ironing, preparing lunch washing the dishes	2	2
[49]	no	4	left and right wrists, waist, right ankle	walking, walking upstairs, walking downstairs, sitting, eating, driving(driver), moving (passenger), standing, lying	9	100
[12]	yes	6	chest, arm, wrist, waist, knee, ankle	lying down, preparing food, eating and drinking, socialising, reading, getting dressed, walking in a corridor, treadmill walking at 2 km/h, vacuuming, wiping tables, running in a corridor, treadmill running at 7 km/h, cycling, sitting down and getting up, lying down and getting up	3	50
[50]	no	6	both lower legs, both lower arms, waist, head	walking, running, rotating arms, jumping jacks, punching	6	60
[24]	no	3	right hand, right thigh, chest	standing, sitting, supine, prone, left lateral recumbent, walking, running, bending forward, left bending, right bending, squats, settlements and lifting the chair, falls, turns left and right, walking upstairs, walking downstairs	3	
[51]	no	5	chest, neck, upper arm, lower arm, hand	upper limb kinematics	6	60
[52]	no	1	dominant wrist	standing, sitting, walking, running, vacuuming, scrubbing, brushing teeth, working at a computer	3	100
[17]	yes	13	lower back, upper back, sternum, waist, both lower legs, both upper legs, both lower arms, both upper arms, head	alpine skiing	9	100
[53]	no	5	sole, heel, toe-cap, instep, ankle	walking, walking upstairs, walking downstairs,	9	20
[54]	yes	1	trunk	lying, sitting, standing flat, standing in elevator downwards, standing in elevator upwards, flat walking, walking downstairs, walking upstairs	6	40
[55]	no	4	chest, left under-arm, right waist, left thigh	lying, sitting, standing, flat walking, walking upstairs, walking downstairs, lying-to-standing, standing-to-lying, sitting-to-standing, standing-to-sitting	3	200
[56]	no	1	pocket, hand	running, slow walking, fast walking, dancing, walking upstairs, walking downstairs	3	100
[20]	yes	5	each wrist, each ankle, chest	walking, running, walking downstairs, walking upstairs, standing, sitting, lying, box and block test, brushing teeth, don jacket, doff jacket, drinking, buttering bread, cutting food, don shoe, doff shoe, peeling carrot, writing	6	50
[23]	no	12	left and right ankle, left and right knee, left and right hip, left and right wrist, left and right above the elbow, left and right shoulder	sitting, standing, walking, walking upstairs, walking downstairs, writing on a whiteboard, typing on a keyboard, shaking hands	3	92
[3]	no	3	under the shoe-laces, lower back	walking a referenced path	3	100
[57]	no	1	wrist	hand washing, drinking	9	
[58]	yes	1	chest	crawling hand and knees, crawling mil., crouching, duck walking, falling, jumping on and off, lying, running, running upstairs and downstairs, sitting, standing, walking, walking upstairs and downstairs, all 4s	6	30
[59]	no	1	chest	crawling hand and knees, crawling mil., crouching, duck walking, falling, jumping on and off, lying, running, running upstairs and downstairs, sitting, standing, walking, walking upstairs and downstairs, all 4s	6	30
[60]	yes	2	toe-cap	walking	6	100
[61]	yes	1	hand (palm)	static, opening door, walking, walking upstairs or downstairs	9	
[62]	yes	1	waist	sitting, standing, lying, walking, walking downstairs and upstairs, running, falling	6	50
[63]	no	1	outside of the right leg over the ankle	walking, standing, climbing upstairs and downstairs	6	100
[64]	yes	1	left shoe	walking straight, walking slope up, walking slope down, walking upstairs, walking downstairs, sitting	9	10
[65]	yes	5	both toe-caps, both lower legs, lower back	walking, running, jogging, pivot, shooting from different locations, layup shot, sprinting, undefined	9	200
[66]	yes	1	pocket of trousers	standing, walking upstairs and downstairs, running upward slope, using elevator	3	1
[67]	no	1	toe-cap	walking, walking upstairs, walking downstairs	9	512
[68]	no	4	left hip, right hip, hip back right, hip back left	falling	6	100

TABLE II. Classification of IMU position on human body based on used acronym names

ID	Defined Name	Acronym Names	Reference(s)
P1	chest	chest, sternum, upper trunk	[27] [34] [41] [43] [45] [46] [9] [13] [12] [24] [51] [17] [55] [20] [58] [59] [26] [54]
P2	back	back, upper backer	[29] [17]
P3	right ankle	right ankle	[11] [39] [22] [49] [20] [23]
P4	left upper leg	left upper leg, left thigh	[11] [35] [38] [39] [47] [17] [55] [9]
P5	left upper arm	left upper arm	[11] [17]
P6	right wrist	right wrist, dominant wrist	[11] [39] [22] [43] [49] [52] [20] [23] [34] [41] [19] [12] [24]
P7	right upper leg	right upper leg, right thigh	[35] [38] [13] [47] [24] [17] [45] [48] [19]
P8	right lower leg	right lower leg	[38] [18] [47] [50] [17] [65] [45] [12]
P9	left lower leg	right lower leg	[38] [18] [47] [50] [17] [65]
P10	left wrist	left wrist	[39] [22] [49] [20] [23] [34] [9]
P11	left ankle	left ankle	[39] [22] [13] [20] [23]
P12	left waist	left waist, left hip, hip	[11] [42] [43] [23] [39] [9] [68]
P13	right waist	right waist, right hip	[42] [55] [23] [40] [22] [16] [48] [19] [12] [68]
P14	left lower arm	left lower arm, left under-arm	[18] [50] [17] [55]
P15	right lower arm	right lower arm, lower dominant arm	[18] [50] [17] [39] [46] [48] [51]
P16	lower back	lower back	[9] [17] [3] [65]
P17	neck	neck	[51]
P18	right upper arm	right upper arm	[17] [48] [12] [51]
P19	left knee	left knee	[23]
P20	right knee	right knee	[23] [12]
P21	left shoulder	left shoulder	[23]
P22	right shoulder	right shoulder	[23]
P23	hip back right	hip back right	[62] [68]
P24	right leg direct over the ankle	right leg direct over the ankle	[63] [48] [64]
P25	upper abdomen	upper abdomen, waist	[25]
P26	left leg direct over the ankle	left leg ankle	[34]
P27	hip back left	hip back left	[35] [68]
P28	foot	left shoe, foot, both feet, boot, barefoot	[64] [47] [21] [14] [46] [38] [30]
P29	sole	sole	[53] [9]
P30	heel	heel	[53]
P31	toe-cap	toe-cap	[65] [53] [60] [67]
P32	instep	instep, under shoe-laces	[3] [53]
P33	right hand	right hand	[24]
P34	head	head	[17]

IV. Conclusion

Our work has shown that the minimum and maximum number of IMUs depend very much on the human activities which had to be detected. In addition, the optimal placement and combination of the IMUs seem to vary depending on the human activities of interest. Therefore, the comparability of the individual solutions is very difficult. This is mainly due to the fact that the studies mostly differ in the range and grain of activities which they want to identify. Another point is that the positioning of the IMUs is not named precisely enough. Partly, the authors use different terms for the same IMU position on the human body. Additionally, in some papers only images are describing the position or the images and the text are contradictory. That means, it is not possible to say that a specific amount and combination of IMUs will always perform best or worst. Nonetheless, if the chosen solution should be able to identify a wide range and more complex movements including writing on a whiteboard or climbing, a multiple sensor system should be favoured.

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