Sensitivity of Sensor Locations in a Wearable IMU-based Human Activity Recognition System

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Research

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Abstract

Background: The advent of Inertial measurement unit (IMU) sensors has significantly extended the application domain of Human Activity Recognition (HAR) systems to healthcare, tele-rehabilitation & daily life monitoring. IMU's are categorized as body-worn sensors and therefore their output signals and the HAR performance naturally depends on their exact location on the body segments.

Objectives: This research aims to introduce a methodology to investigate the effects of misplacing the sensors on the performance of the HAR systems.

Methods: The properly placed sensors and their misplaced variations were modeled on a human body kinematic model. The model was then actuated using measured motions from human subjects. The model was then used to run a sensitivity analysis.

Results: The results indicated that the transverse misplacement of the sensors on the left arm and right thigh and the rotation of the left thigh sensor significantly decrease the rate of activity recognition. It was also shown that the longitudinal displacements of the sensors (along the body segments) have minor impacts on the HAR performance. A Monte Carlo simulation indicated that if the sensitive sensors are mounted with extra care, the performance can be maintained at a higher than 95% level.

Conclusions: Accurate mounting of the IMU's on the body impacts the performance of the HAR. Particularly, the transverse position and rotation of the IMU's are more sensitive. The users of such systems need to be informed about the more sensitive sensors and directions to maintain an acceptable performance for the HAR.

1. Background

Human activity recognition (HAR) systems, particularly those based on body-worn sensors such as inertial measurement units (IMU), have been proven to be of broad demand and application in healthcare, tele-rehabilitation and daily life monitoring [1]. IMU sensors incorporate accelerometers, gyroscopes, and magnetometers to provide valuable kinematic information about the body on which they are mounted [1, 2]. HAR systems utilize the aforementioned kinematic data through hard-coded rules or machine learning techniques [3].

Supervised learning algorithms are usually used in the development of HAR systems with higher numbers of activities [1, 3–5]. These techniques employ labeled data collected from previous experiments to develop mathematical rules capable of classifying new data sets into the previously defined classes [3, 6]. An acceptable rate of activity recognition for the HAR systems is above 80% [4]. Supervised statistical learning methods have been successfully used for activity recognition, similar to simple ANNs or radial basis function networks [7]. Lately, deep learning approaches have also been proven to be highly convenient in the field of activity recognition, especially when it comes to real-time classification, demanding low latency [8–10].

In a previous study [11], the capability of recognizing activities for healthy people in an IMU-based tracking system comprising ten sensors, was investigated. The best classifier, based on the Nearest Mean (NM) algorithm, obtained 94.3% precision using four IMUs. An adaptation algorithm was also proposed to maintain the precision of recognition above 90% when the system was used on a new subject. The system was developed for recognizing 34 mobility exercises for PD patients comprising LSVT-BIG home training and some functional movements [12, 13].

All of the supervised learning techniques are dependent on the training data, therefore, any position error in mounting of the sensors (sensor misplacement) on the body segments may reduce the accuracy of the recognition in real applications [3]. This has been experimentally investigated in a few studies [14, 15]. In these works, the activities were repeated by the subject in several trials where the sensor positions were slighty altered. However, such fully experimental approaches are difficult to carry out since they require neumerous experiments. Also, one should note that in such cases, the recognition accuracy is always influenced simultaneously by the sensor misplacements and natural variations in the performance of the tasks by the human subjcts. This complicates making any independent conclusions on how the sensor misplacement impacts the HAR performance. Also, it seems that the primary target in these studies has been how the effects of the placement error can be mitigated through recallibration rather than understanding the sensitivity of the HAR performance to the sensor placement [16].

This study investigates the sensitivity of the sensor misplacements, in the above-mentioned HAR system, on the accuracy of activity recognition, using a hybrid approach. A limited number of experiments were carried out and a kinematic body model was built and used to extend the data. Th motivation of this study is to use the sensitivity analysis results to provide a guideline for the system users to improve the functionality of the HAR system.

The paper outline is as follows: In the method section, the proposed IMU-based system, the 3D CAD model, and the process used for sensor misplacement analysis is explained. It is followed by the results and the discussion, highlighting the most sensitive sensors in the HAR system, the user guidelines determining the sensors placement protocol for the the system, and the overall evaluation of the HAR system.

2. Results

For the participating subjects, the *PPV* of activity recognition for the validation tests and the variation tests are reported in Table 1. As can be seen, the precision of activity recognition for all subjects in the validation tests equals 1 (100%). This table suggests that the 3 most sensitive types of misplacements are: transverse variations for left arm, right thigh and rotational variations for left thigh.

Table 1
The PPV of the original HAR system and the ones with misplaced sensors

			Subject 1	Subject 2	Subject 3
	Validation precision (original system without sensor misplacements)		1	1	1
The least precision of recognition for the variations	Longitudinal variations	Right Arm	1	1	1
		Left Arm	1	1	1
		Right Thigh	1	1	1
		Left Thigh	1	1	1
	Transverse variations	Right Arm	0.987	1	1
		Left Arm	0.987	0.950	0.987
		Right Thigh	0.987	0.962	1
		Left Thigh	1	1	1
	Rotational variations	Right Arm	1	1	1
		Left Arm	1	1	1
		Right Thigh	0.987	1	1
		Left Thigh	0.987	0.987	1

Table 2 shows the minimum misplacement variations that result in a drop of *PPV*. Empty cells indicate that the *PPV* was maintained even with the maximum displacement of the corresponding type. The displacement variations were 0 to 20 mm for longitudinal and transverse directions and 0 to 8 degrees for the rotation of the sensor.

Table 2
The minimum misplacements that results in PPV drop

		Subject 1	Subject 2	Subject 3
Longitudinal variations	Right Arm	-	-	-
	Left Arm	-	-	-
	Right Thigh	-	-	-
	Left Thigh	-	-	-
Transverse variations	Right Arm	20 mm	-	-
	Left Arm	15 mm	15 mm	20 mm
	Right Thigh	15 mm	15 mm	-
	Left Thigh	-	-	-
Rotational variations	Right Arm	-	-	-
	Left Arm	-	-	-
	Right Thigh	8 degrees	-	-
	Left Thigh	8 degrees	8 degrees	-

The performance of the HAR system, in the presence of a combination of sensor misplacements, was disclosed by a Monte Carlo simulation and is shown in Table 3. The table also shows how the system performance differs when the sensitive types of misplacements are treated with more caution by reducing their standard deviations through a sensor mounting guideline.

Table 3
The overall system PPV (%) in the presence of multiple misplacements calculated by a Monte Carlo simulation. In the first column, the distribution functions for all misplacement types are identical, the second column is the results for revised distribution based on the sensitivity of the sensors.

	Similar distribution for all misplacement types	Revised distribution for sensitive sensors
Subject 1	88	97
Subject 2	93	98
Subject 3	95	99

3. Discussions And Conclusions

The core idea of the present work is to use a 3D model of the human kinematics for sensitivity analysis of the IMU sensor placements in a HAR system. The main motivation was to avoid excess number of experiments which brings other uncertainties such as repeatability of the tasks by the users. For this reason, older studies in this area, such as those mentioned in the background section, were not able to distinguish between the effects of the natural human variations in task performance from the sensitivity of the HAR to the sensor locations.

Tables 1 and 2 suggest that the transverse displacement of the left arm and the right thigh sensors and rotation of the left thigh sensor have the highest impacts on the precision of the HAR system. Table 2 also shows that the transverse misplacements are more sensitive since their smaller values start decreasing the PPV of the HAR. The results also suggest that the longitudinal misplacements of the sensors have minimal impact on the performance of the HAR system within the considered interval (± 20 mm). Although higher values may start reducing the performance of the system, they are unlikely to occur since they can be easily noted and avoided by the wearer of the device. As a sensor installation guideline, it can be concluded that the transverse location of the sensors of the left arm and right thigh and the sensor orientation of the left thigh are the most sensitive ones and should be treated with extra care when wearing the sensors.

Using a Monte Carlo simulation, the impact of the combinations of the sensor misplacements was investigated. Also it allowed us to predict how the installation guidelines may improve the overall outcome of the HAR. As shown in Table 3, the combined effect of sensor misplacements is a drop of 5–10% in the PPV. The second column of the same table, however, indicates that when the installation guideline was implemented (by reducing the standard deviation of the sensitive misplacements by a factor of 3), the PPV was improved by about 5–9% which approves the effectiveness of the sensitivity analysis at least through the simulation.

The pattern of sensitive misplacement types was similar among the three subjects participating in the study although the intensity was slightly different. This implies that personal habits in performing physical activities may influence the amount of sensitivity of the sensor placements. A detailed study is required to characterize this dependency and its implication on the HAR performance which is among the future works of this research.

4. Methods

The outline of the whole sensitivity analysis process is shown in Fig. 1. A 3D CAD model of the human body was built and actuated using real joint angles data from normal subjects. The joint angles were collected using a standard motion capture system (Vicon system + Plugin-gait protocol). Each subject performed eight activities (as will be explained later in part one of the Methods section) for ten times to provide a set of movements with natural variations. Virtual sensors were installed on the CAD model. The virtual sensors were coordinate systems that could be defined at any arbitrary location on the CAD model. The accelerations, and angular velocities of the virtual sensors were extracted (with respect to the local

frames of the sensors) and were used as inputs to the HAR system. The precision of the HAR system was then calculated and considered as the performance index.

4.1. The HAR system and the activities

The HAR system used in this research had been developed in a previous study and was composed of four IMU sensors [11]. The system was to recognize a set of 34 activities for physical rehabilitation of Parkinson's disease (PD) patients. The activities included LSVT-BIG [12] and some functional exercises. Due to similarities in the nature of these activities, only 8 of them were later used as representatives for the sensitivity analysis, namely: slow-walk, picking up, putting down, turning to left, LSVT-BIG step forward and reach (right and left), LSVT-BIG step to the side and reach (right and left). For more information about the activities see [11].

In the HAR system, eight features were calculated from the linear accelerations and angular velocity components from each of the four sensors. The features were in the time, frequency, and the time-frequency domain (see [11]). A combination of the principal component analysis (PCA) and linear discriminant analysis (LDA) was used for feature extraction [17]. In this method, the redundant features were elided using the PCA, then the best features for classification were extracted using the LDA. Finally, the nearest mean (NM) algorithm [11, 18] was used to categorize the activities. The HAR system used a two-stage training procedure. It was once trained with a database of nine subjects. Then for each particular user for whom the recognition was to be done, a re-training or so called adaptation was performed using the data collected from the same person. For this purpose, each new subject had to perform the activities for a minimum of six times in the presence of a trained staff to make sure that the sensors were correctly attached and the activities were performed correctly. The collected data were then replicated and added to the original database. The replication was done to increase the weight of the subject’s data versus the old data in the database. The augmented database was then used to re-train the classifier to maximize the performance for that particular subject. In other words, the second training phase, customized the classifier for each individual. This was justified since the final application of the proposed system is tele-rehabilitation and therefore, the device is supposed to be lent out to the same individual for a certain period of time.

The participants in the current study (3 male subjects aged 23–28), performed the eight mentioned activities for ten times each, under the lab staff supervision. While the subjects performed the activities, motion capture was performed following the Plug-in gait model. The data of motion capture analysis was further used to re-train and test the HAR system. In order to do so, the joint angle data were used to actuate the CAD model and the IMU data was extracted from the model. This process will be fully demonstrated in the following section. Figure 2 shows the experimental setup.

4.2. A 3D CAD body model and actuating the model

A kinematic anthropometric 3D CAD model of a human male body [19] was used to investigate the effects of the sensor misplacements. The model, as shown in Fig. 3, has a total of 15 segments (head,

thorax, pelvis, bilateral feet, shanks, thighs, arms, forearms, and hands) and 14 joints (neck, spine, bilateral ankles, knees, hips, shoulders, elbows, and wrists). The CAD model was imported to Simulink-MATLAB R2016a for kinematic simulation.

Using the motion capture analysis (Vicon and plug-in gait model), the joint angles according to the plug-in gait model were extracted from the experiments. Such angles are in the form of Euler angles that correspond to the coordinate frames of the successive segments. The Euler angles were then input to the CAD model. For this purpose, frame assignments were carried out on the CAD model segments following the Plug-in gait model. As a result, the model was able to replicate the movements of each subject in the simulation environment.

4.3. Modeling the sensor misplacements

In the CAD model, the IMU sensors were modeled by body-attached small cubes each incorporating a local frame. The frames were defined such that their z-axes were normal to the model surface. The acceleration and the angular velocity vectors of the segment were measured in accordance to the local frames by the simulation software, resembling the IMU sensors outputs. In this study, the selected regions to install the IMU sensors, were the right and left arms & right and left anterior thighs. The gravitational acceleration was also added separately to the sensors' output for full resemblance with real IMUs.

In this research, three types of sensor misplacements were implemented on each sensor, namely: Translations in the longitudinal and transverse directions of the body segment, and rotation about the z-axis of the sensor (normal to the body surface). Considering four sensors and three types of misplacements for each and ignoring any interactions between the different types of sensor misplacements, a total of twelve types of misplacements were considered and analyzed. For the longitudinal and transverse directions, eight steps of displacements were considered with a step size of 5 millimeters resulting in an overall range of 40 millimeters with the nominal sensor placement at the center. Note that these displacements are accompanied by small rotations of the sensor as well since the sensor is constrained to lie on the surface of the body segment. Figure 4 depicts the proposed locations for mounting the sensors for arms and legs. The rotational misplacement of the sensors (about the z-axis) were implemented by multiplying a rotation matrix to the output vectors of the central sensors. Eight rotation steps of two degrees were considered resulting in a variation interval of − 8 to 8 degrees.

The proposed variation ranges for the sensor misplacements were determined based on the common sense. It was noted that translations greater than 20 mm in any direction or rotations more than 8 degrees were quite apparent and easily noted by the user and hence corrected before using the HAR system.

4.4. Sensitivity analysis

The purpose of the sensitivity analysis was to determine the impact of each of the 12 types of sensor misplacements on the performance of the HAR system. The performance of the HAR system was

measured using precision [1] or positive predictive value (PPV). This measure is a good indicator of the overall functionality of the classifier for the whole set of activities [1]. PPV was calculated as:

$$PPV = \frac{\sum T_p}{\sum(T_p + F_p)}$$

where, T_P (true positives) represents the number of correct recognitions of classes in samples of positive conditions, and F_P (false positives) represents false classifications of samples with positive conditions. T_P & F_P are extracted from the confusion matrix.

The HAR system used in this study underwent an adaptation process. 2 of 10 instances for each of 8 activities performed by each subject, were replicated and used to adapt the HAR system to the same subject (as discussed in Sect. 2.1). For the adaptation phase, the outputs of the nominal sensors were used. The remaining 8 instances of the activities performed by the subject were used to validate the HAR system with sensors at their nominal locations ("validation tests").

In order to determine the sensitivity of the sensor misplacements, the data extracted from the misplaced sensors were fed to the HAR system. Such experiments are called "variation tests" in this work. In each variation test, all 10 instances of activities performed by the subject in which 1 and only 1 out of 12 types of misplacement was applied were produced by the model and sensors' outputs were processed by the HAR.

For investigating the effects of each one of the 12 types of misplacement, we compared the *PPV* of the variation tests with that of the validation tests for each subject. The higher the difference is, the more sensitive that type of the misplacement would be.

In reality, there are always combinations of different types of misplacements. As a result, it remains to determine how the interaction between different types of misplacements impact the performance of the HAR. For this purpose Monte Carlo method was used [20]. Following this method, misplacements of the sensors were considered as random variables and their impact on the system performance was determined statistically through simulations. In this study, two sets of distribution functions were considered for the sensor misplacements. In the first set, we assumed similar distribution for all misplacement types. In the second set, we assumed that the user was provided with some guidelines on the importance of the top three types of misplacements out of the 12 types. This guideline was assumed to be resulted from the sensitivity analysis. Therefore, it was expected that users mount the more sensitive sensors more accurately. To perform the process, 200 random instances of the sensor mounting on the human body were modeled by a discrete normal distribution. The placement of sensors was computed by the formula below:

$$X_{placement} = \mathcal{N}(X_{mean}, \sigma)$$

where $\mathcal{N}$ is a normally distributed random variable with a mean of X_{mean} (i.e. the nominal location of the sensor) and standard deviation of σ. The standard deviation was set to the range of variation used in the sensitivity analysis for all 12 misplacement types. Using the above distribution of the misplacement, 200 instances of the sensor placements were built and output signals were fed to the classifier. The average precision rate was calculated and considered as the overall performance of the system in the real world applications where a combination of sensor misplacements is present. In a second set of simulation, for the first three misplacement types with top sensitivity, the standard deviation was reduced to one third assuming that the user instruction of the system recommends more precise mounting of the corresponding sensors. The results are to determine how the outcome of the sensitivity analysis may impact the performance of the system through more accurate mounting of the sensitive sensors.

5. Abbreviations

Inertial measurement unit (IMU), Human activity recognition (HAR), Nearest mean (NM), Parkinson's disease (PD), Principal component analysis (PCA), Linear discriminant analysis (LDA), Positive predictive value (PPV)

6. Declarations

Ethics approval and consent to participate: The Ethics committee of Iran University of Medical Sciences approved all protocols. All participants provided written confirmed consent according to the Declaration of Helsinki.

Consent for publication: Not applicable.

Availability of data and material: The data used during the current study are available from the corresponding author on reasonable requests.

Competing interests: The authors declare no competing interests.

Funding: Not applicable.

Authors' contributions: ME designed and performed the experiments, performed the mathematical modeling, analysis and interpretation of the data, drafted and revised the manuscript. AMN and SB substantially contributed to the methodology development, and revising the manuscript. All authors read and approved the final manuscript.

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7. References

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Figures

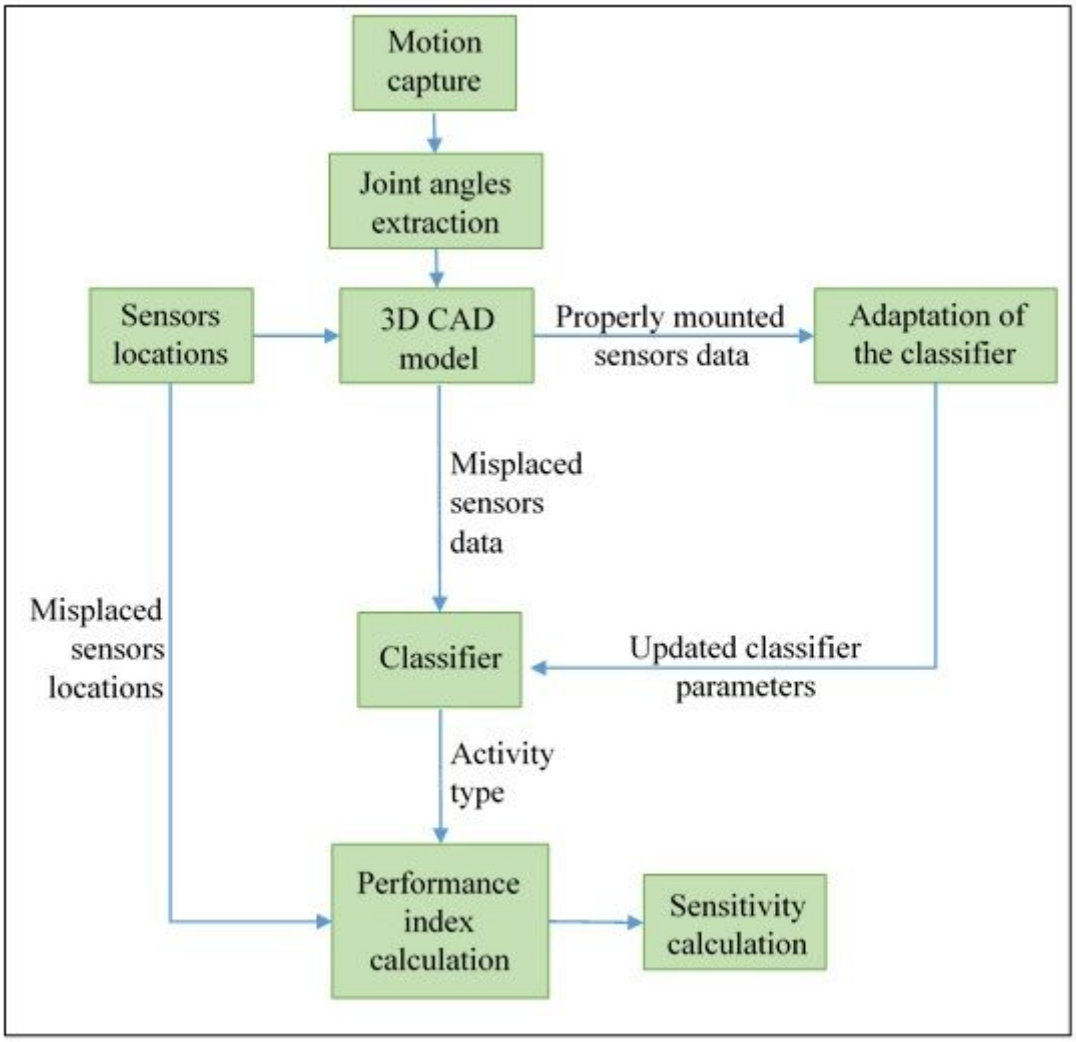

Figure 1

The process of sensitivity analysis of the HAR system for IMU sensors misplacement.

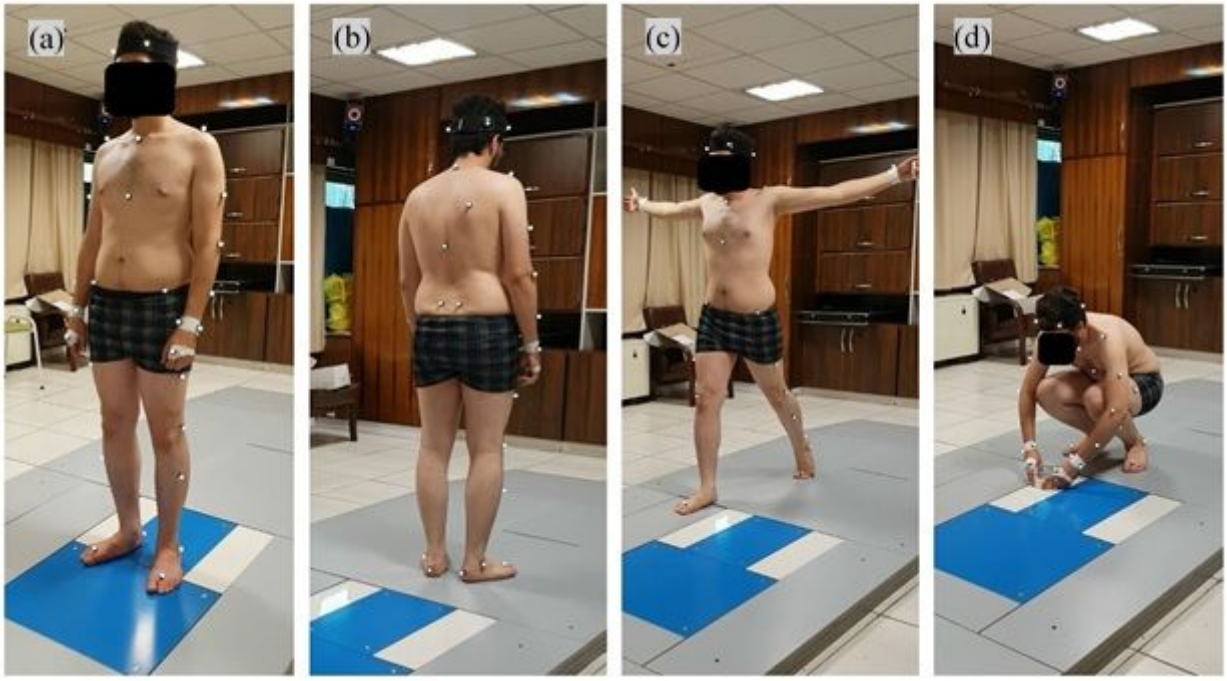

Figure 2

a, b) Marker placement according to plug-in gait protocol. c) LSVT-BIG step forward and reach (right) activity. d) picking up activity.

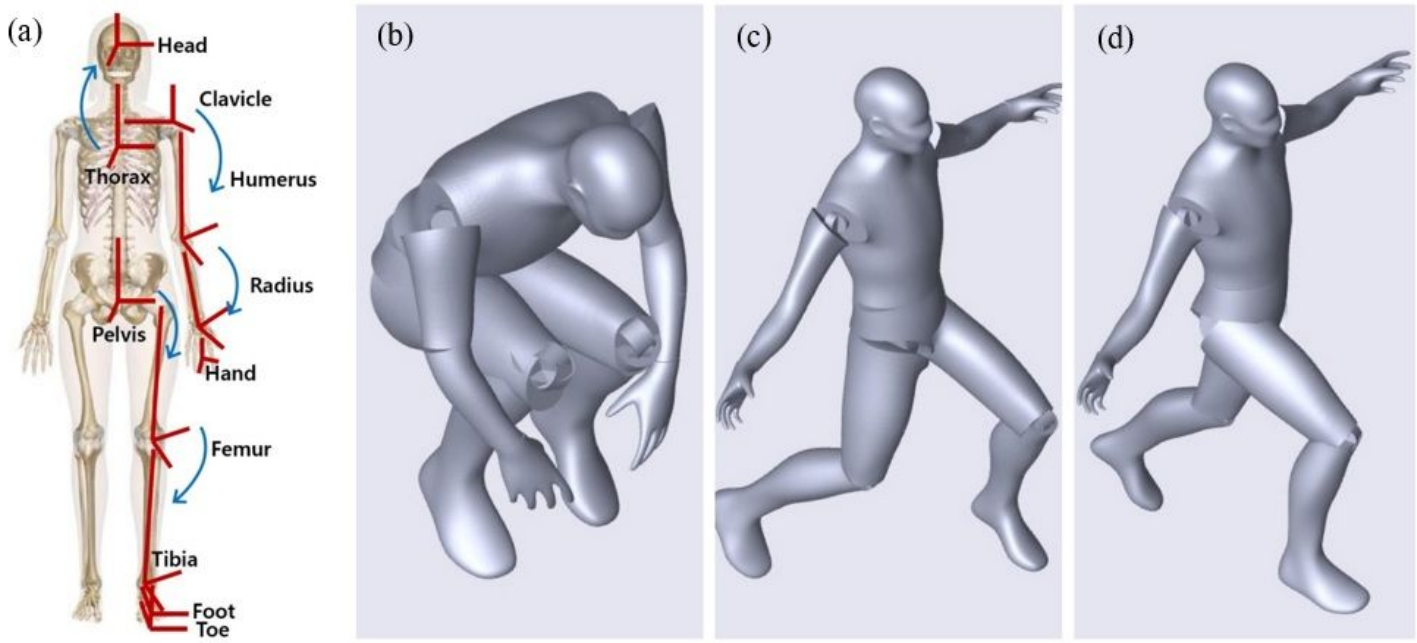

Figure 3

a) The segment definition and the segment-attached coordinate systems according to the Plugin-gait model [21]. b, c, d) instances of the simulated tasks: picking up, LSVT-BIG step forward and reach (left & right)

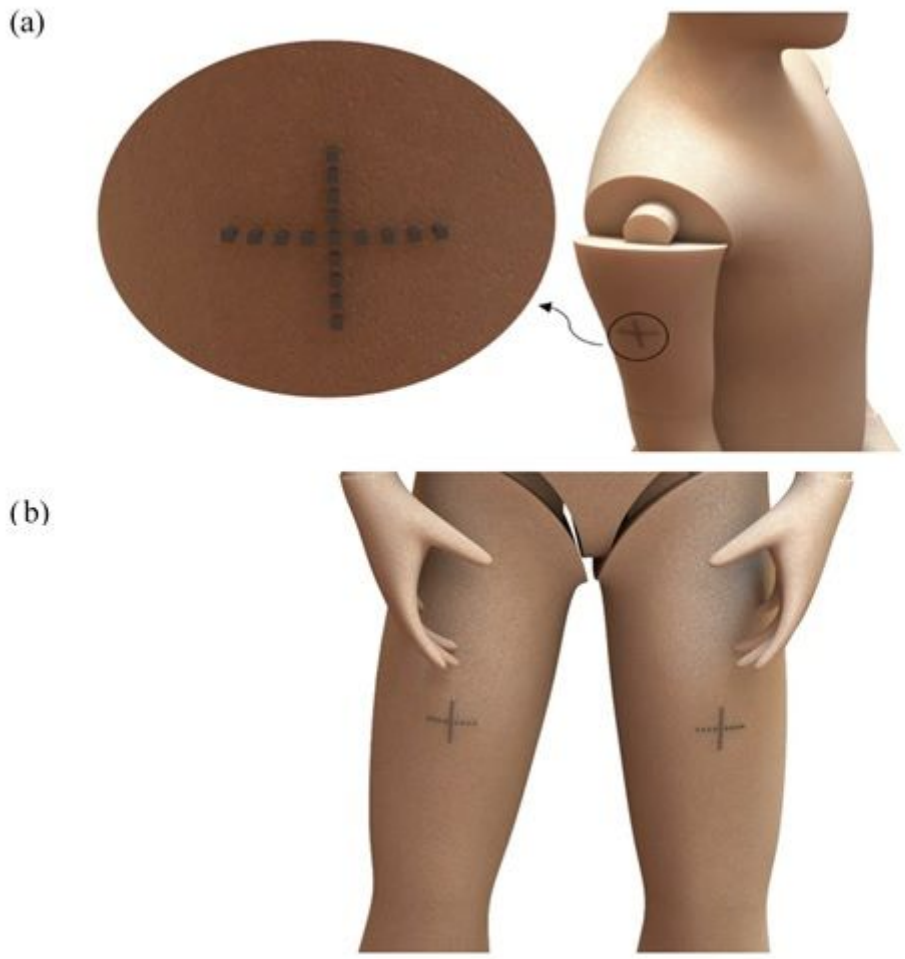

Figure 4

a) The proposed variations for the mounting locations of the sensors of the right arm. The sensor at the center of the cross is at the nominal position; Other sensors are placed 5 millimeters apart in the longitudinal and transverse directions of the right arm. Considering a nominal sensor and its displacements, there are 17 cubes (representing sensors) in each sensor region. b) The installation of the properly mounted sensors and their translational variations on the right and left anterior thighs.