Location Determination of On-body Inertial Sensors

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Abstract: Human Activity Recognition has gained tremendous drive in recent years. This is due to the increasing ubiquity of all types of sensors in commodity devices such as smartphones, smart watches, tablets, etc. This has made available to the normal user a continuous stream of data including visual data, inertial motion data, audio, etc. In this paper we focus on data streamed from inertial motion units (IMUs). Such units are currently embedded on almost all wearable devices including smart watches, wrist bands, etc. In many research works, as well as in many real applications, different specialized IMU units are mounted on different body parts. In the current work, we try to answer the following question: given the streamed inertial signals of a gait pattern, as well as some other activities, determine which sensor location on the subject's body generated this signal. We validate our work on several datasets that contain multi-dimensional measurements from a multitude of sensors mounted on different body parts. The main sensors used are the accelerometer and gyroscope. We use the Random Forest Classifier over the raw data without any prior feature extraction. This has proven yet very effective as evidenced by the results using different metrics including accuracy, precision, recall, F1-score, etc. An important application of such research can be in data augmentation of timeseries inertial data. This can be used as well for healthcare applications, for example, in treatment assessment for people with motion disabilities.

1 INTRODUCTION

Human Activity Recognition (HAR) is a field of research that boomed in popularity in recent years with the ubiquity of wearable smart devices such as smart watches and smartphones. Using the inertial sensors (such as accelerometers, gyroscopes and magnetometers) embedded inside these devices, the motion dynamics of different activities can be recorded, streamed to a processing unit, and be analyzed to recognize the action the current user is doing. Similarly, recent research showed also that the identity of the user can be identified using these sensors during one of the most common activities done throughout the day, i.e. walking (Adel et al., 2020).

Nevertheless, since these devices can be used in so many different contexts (e.g. sports, medical purposes, research purposes), they can be placed on different locations on human body (wrists, legs, arms, etc.). The variety of places that these sensors can be placed on can greatly affect the accuracy of human activity recognition or person identification. Meanwhile, detecting sensor placement has not attracted enough attention in research and has been done implicitly in few works on few common places (such as right and left pockets and right and left hands only) (Primo et al., 2014).

In this paper we focus on the detection of location of on-body inertial sensors using Random Forest Classifier during various activities using four different publicly available datasets that use inertial sensors (accelerometer and gyroscope included). The contributions of this work are as follows:

- We present a full detection of inertial wearable sensors on different parts of human body during various activities on four different datasets.
- We work on raw inertial data without any feature extraction algorithms.
- We achieved an average accuracy of 92.33% on all the four datasets.

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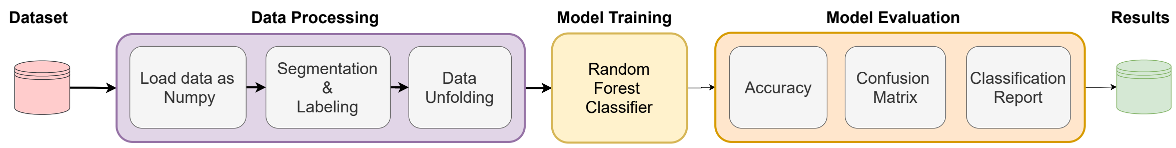


Figure 1: Experiments pipeline.

The rest of the paper is organized as follows. Section 1 as introduction. The related work is presented in Section 2. Then, we explain our proposed methodology in Section 3, which we explain in it the experiments pipeline shown in Figure 1. After that, we show our experiments in Section 4. Our results and discussion are presented in Section 5. Finally, Section 6 is the conclusion of our work and the future plans.

2 RELATED WORK

(Kunze et al., 2005) managed to derive the location of the acceleration sensor on the user's body using the sensor's signals only. Their algorithm in detecting the location of the sensor is not affected by the sensor's orientation. Using this algorithm, they managed to identify the time periods where the user is walking and then by using the unique characteristics of walking they could identify the location of the sensor on the user's body. The fact that the location of the sensor is an interesting context was what motivated them to do this work. In addition to that, They denoted that the locations of the sensors was chosen according to regularly used devices and sensors. They used four classifiers: C 4.5, Naive Bayes, Naive Bayes simple and Nearest Neighbor. The experiments were on 6 subjects. They conducted 3 runs each run was between 12 and 15 minutes with 8 activities performed. The senors were placed on 6 different body parts: wrist, right side of the head, left trouser's pocket and left breast pocket. The C 4.5 classifier got the highest accuracy among the four used classifiers by accuracy 89.81%.

On the other hand, (Vahdatpour et al., 2011) used accelerometers to capture the motion data of subjects' actions. This data allowed them to detect the location of the sensor on the subject's body by using a mixed supervised and unsupervised time series analysis model. They used Support Vector Machine (SVM) algorithm to identify the sensors' locations. Furthermore, they used their own dataset which consisted of 25 subjects with sensors mounted on 10 different places on the body. Those 10 places were classified into 6 regions: forearm, upper arm, head, thigh, shin and waist. In their first conducted experiment, they trained and tested the SVM on each subject separately with training and testing ratio 2:8. The results were 88%, 98% and 100% for the minimum, mean and maximum precision, respectively. In the second conducted experiment, they trained the model on randomly chosen segment from different subjects and the average accuracy for this experiment was 89%.

In (Sztyler and Stuckenschmidt, 2016), the authors presented a dataset with 17 subjects with 8 performed activities, each subject wore 7 sensors on the head, chest, upper arm, waist, forearm, thigh and shin. They used acceleration sensor's data like the previous two works to identify the sensor's location by using a Random Forest Classifier. They introduced their method for the location identification by treating the position as a multi class classification problem that made the sensors' locations the targeted classes. They conducted their experiments on each subject individually, as they reasoned, due to the difference in individual behaviour and ages. After they had conducted the experiments, they achieved an average performance accuracy of 89% across all positions and subjects.

The authors in (Weenk et al., 2013) introduced an automatic identification method for inertial sensors on different body parts during walking. This introduced method allows the user to place inertial sensors in a full body or lower body plus trunk configurations. The number of sensors that implemented by the user ranges from 17 to 8 inertial sensor in the mentioned places respectively. Based on the acceleration and angular velocity data extracted from the user's walking for a few seconds, the identification process is automatically done. Their dataset is composed of 11 healthy subjects performed 35 walking trials, and then tested on 7 patients after a reconstruction surgery in their knee. The authors extracted RMS, variance, correlation and inter-axis correlation co-efficients features from magnitudes and the 3D components of the acceleration, angular acceleration and angular velocity. In their experiments, the authors used J4.8 decision tree algorithm as their classifier. J4.8 is an implementation for C 4.5 algorithm which is the same classifier used in (Kunze et al., 2005). Their process gets 100% for lower body sensors plus trunk configurations and 97% for full body sensors.

In this work, however, we conduct our experiments on four publicly available datasets with varying number of subjects and activities using a Random

Forest Classifier trained on the raw inertial data of accelerometer and gyroscope only. We also achieve state-of-the-art performance in comparison to the previous works.

3 PROPOSED METHODOLOGY

In this section, we will explain briefly the different stages of our proposed methodology. As can be seen in Figure 1, we start by loading the datasets before performing any processing on them in the preprocessing stage. Next, the data is fed to a machine learning classifier model for training. After the model is trained, we evaluate our model using different metrics on a test set and report our results.

3.1 Data Preprocessing

The data preprocessing stage consists of three steps: loading the data, data segmentation and labeling, then data unfolding.

In the first stage, we make sure that all dataset files are converted to Numpy arrays. This is because each dataset we use has a different file structure and a different file format, it is an important step to unify all these datasets in one common format.

Each IMU data file consists of $R \times C$ matrix, where R is the number of timesteps, and C is the number of axes or channels (i.e. 6 channels for a 3-axis accelerometer and 3-axis gyroscope). We iterate over each data file for each IMU device and segment the data into 3-second fixed-length segments. For example, if the sampling rate is in our dataset is equal to 50 Hz, our final segments will be 150×6 matrices. For each data segment, we construct a label y corresponding to the IMU device from which the data was recorded. Hence, if we have M segments, we end up with M labels as well. To be able to use the data segments in our machine learning model, we unfold each data segment into a 1-D vector $x \in \mathbb{R}^{RC}$. Therefore, the output of the preprocessing stage is a $M \times RC$ data matrix X, and a M-dimensional labels vector y.

3.2 Model Training

After the data preprocessing stage, the data is ready to be fed to the model. We train a Random Forest Classifier to predict the location of the IMUs in a number of datasets. Random Forest Classifier is a ensemble classifier that uses a large number of decision trees classifiers on features selected randomly from the training data, and then use averaging to improve the prediction accuracy and control over fitting (Breiman, 2001). In our model, We set the number of decision trees to 500, use the gini index which is the function that measures the quality of a split. We set the minimum number of samples to split to 2 samples and used bootstrapping.

3.3 Model Evaluation

After training the model, we then evaluate it on a test set using four different metrics: the accuracy, precision, recall and F1-score.

We calculate the test accuracy of the model as follows:

$$accuracy = [\frac{1}{N}\sum_{i=0}^{N-1} 1(\hat{y}_i = y_i)] \times 100\% \qquad (1)$$

where y_i is the test label number i, $\hat{y}_i$ is the predicted label number i and N is the total number of samples in the test set. The expression $1(x_i = y_i)$ is called indicator function which indicates the membership of $\hat{y}$ in y.

We calculate the precision and recall using the following formulae:

$$precision = \frac{TP}{TP+FP} \qquad (2)$$

$$recall = \frac{TP}{TP+FN} \qquad (3)$$

where TP is the number of true positives, FP is the number of false positives and FN is the number of false negatives for each class. The precision ratio shows the classifiers ability to avoid labeling a positive sample as negative while the recall ratio shows the ability of the classifier to correctly find all the positive samples.

On the other hand, The F1-Score is the harmonic mean of precision and recall. The F1-Score is calculated as:

$$F_1 = 2 \times \frac{precision \times recall}{precision + recall} \qquad (4)$$

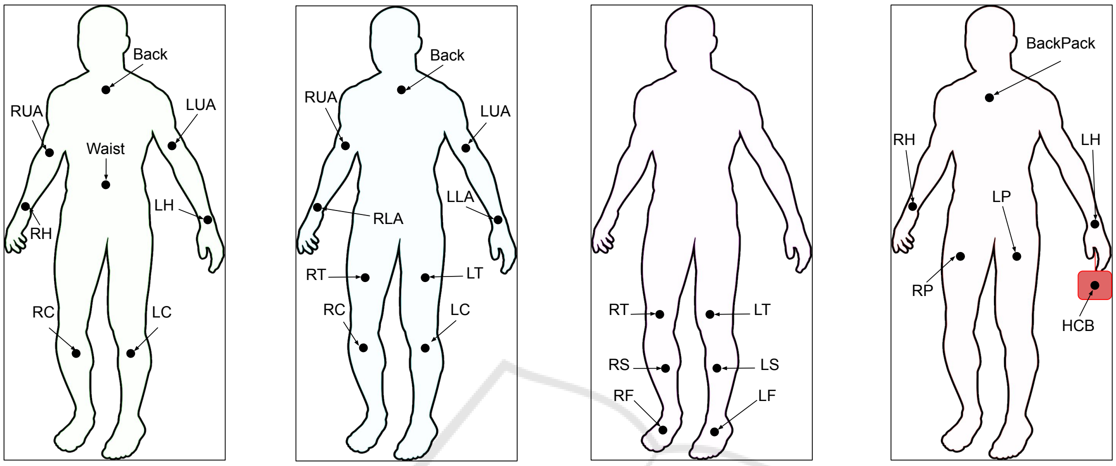
The F1-score is a single number that incorporates both the prevision and recall. Its maximum value is 1 when the model has perfect precision and recall. The minimum value is 0 when either the precision or recall is zero.

4 EXPERIMENTS

In our experiments we apply the steps mentioned in Section 3 on four publicly available datasets: EJUST-GINR-1, RealDisp, HuGaDB and MMUSID. Each

Table 1: Datasets summary.

Datasets	No. of samples	No. of sensors	No. of activities	Body parts				Other	
				Back	Waist	Legs	Arms	BP	HCB
EJUST-GINR-1	46236	8	1	1	1	2	4	-	-
RealDisp	148698	9	33	1	-	4	4	-	-
HuGaDB	70980	6	12	-	-	6	-	-	-
MMUSID	26924	6	1	-	-	2	2	1	1



(a) EJUST-GINER-1 (b) RealDisp (c) HuGaDB (d) MMUSID

Figure 2: Datasets Sensors' Locations.

dataset has a slightly different number of devices mounted on different locations on human body as shown in Figure 2. We load each dataset then feed 75% of the raw data (without any feature extraction) to our Random Forest Classifier to train on and finally, we evaluate our model on 25% of the data reporting the four measure dicussed in Section 3.3.

4.1 Datasets

In this section we give a brief overview of the datasets used in our experimentation. The highlights of the four datasets are summarized in Table 1.

4.1.1 EJUST-GINR-1

EJUST-GINR-1 dataset consists of 8 IMUs each unit streams tri-axis accelerometer and tri-axis gyroscope data with a sampling rate of 50 Hz. Gait data is collected from 20 subjects, 10 males and 10 females (Adel et al., 2020) and the sensory units are located on 8 different body parts as show in Figure 2a.

4.1.2 RealDisp

The RealDisp dataset consists of 9 IMUs each streams tri-axis accelerometer, tri-axis gyroscope and tri-axis magnetic field readings, in addition to orientation estimates in 4D format with sampling rate of 50 Hz. The data is collected from 17 subjects with 33 activities. There are three scenarios for placing the sensors: Ideal, Self and Mutual. In the ideal scenario, the instructor places the sensors in the predefined places on the subject's body. In the self scenario, the user is asked by the instructor to position 3 sensors on the specified locations. In the mutual scenario, the instructor introduces an intentional disposition of a number of sensors (4 to 7 sensors) using rotations and translations with respect to the ideal case (Banos and Tóth, 2014). In our experiment we only use the ideal scenario files. The sensors are located on 9 different body parts as shown in Figure 2b.

4.1.3 HuGaDB

HuGaDB dataset consists of 8 units, 6 units are inertial sensor units streaming tri-axial accelerometer and tri-axial gyroscope readings while the other two are EMG sensors. The data is collected from 18 subjects with 12 different activities (Chereshnev and Kertész-Farkas, 2017). In our experiment we used only the inertial sensors readings which are located mainly on 6 different parts of the leg as shown in Figure 2c

4.1.4 MMUSID

MMUSID consists of 6 sensor units each streaming tri-axial accelerometer and tri-axial gyroscope readings for 120 subjects with sampling rate of 50 Hz. The dataset includes only the walking activity but with different speeds: slow, normal and fast walking (Permatasari et al., 2020). The sensors in this dataset are placed in places that mimic the real life such as in a backpack, hand-carried bag, right and left pockets and right and left hands as shown in Figure 2d.

5 RESULTS AND DISCUSSION

5.1 Results

In this section we report the results of our experiments on each dataset separately. We constructed a confusion matrix for our model on each dataset showing the cross-accuracy between the classes while the the vertical axis is the ground truth and the the horizontal axis is the prediction. The confusion matrices for all datasets are shown in Figure 3a, Figure 3b, Figure 3c and Figure 3d. It is clear from the diagonal of the four confusion matrices that the model could observe all the sensor places with high accuracy in all the datasets. Moreover, as we see in Table 2, the model has a test accuracy over all classes for EJUST-GINR-1, RealDisp, HuGaDB and MMUSID of 92.86%, 84%, 93.98% and 98.49%, respectively.

5.1.1 EJUST-GINR-1

The EJUST-GINR-1 dataset has 8 sensors that are placed in 8 different body parts. From the confusion matrix shown in Figure 3a we could observe that the Left Calf (LC) and Right Calf (RC) have the highest detection accuracy among the 8 sensors and the confusion between their place detection is nearly negligible. The Right Hand (RH) and Left Hand (LH) sensors have some confusion in their place prediction, but does not have any conflict with any other sensor. The Right Upper Arm (RUA) and the Left Upper Arm (LUA) have confusion between them only by accuracy of 12.195% and 13.800%, respectively. The Waist and RUA have a noticeable conflict between each other by accuracy of 3.579% and 2.826%, respectively.

5.1.2 RealDisp

The RealDisp dataset has 9 sensors in 9 different places. From the confusion matrix in Figure 3c, we observe some confusion between sensors locations. The RUA and Right Leg (RL) both have noticeable miss-classified cross predictions between each other by about 6.674% and 6.993% accuracy, respectively. Similarly, we have the Left arm sides LLA and LUA miss-classified cross-predictions by 6.510% and 6.211%, respectively. The LUA and RUA have miss-classified cross predictions by 4.197% and 5.628%, respectively. Nevertheless, the other miss predictions are surprisingly almost negligible. On the other hand, for the lower part of the body, we have the Right Thigh (RT) and the Left Thigh (LT) having prediction confusion by about 6.950% and 7.868%, respectively, while we have the RC and LC confusion by about 8.038% for RC and 7.249% for LC.

5.1.3 HuGaDB

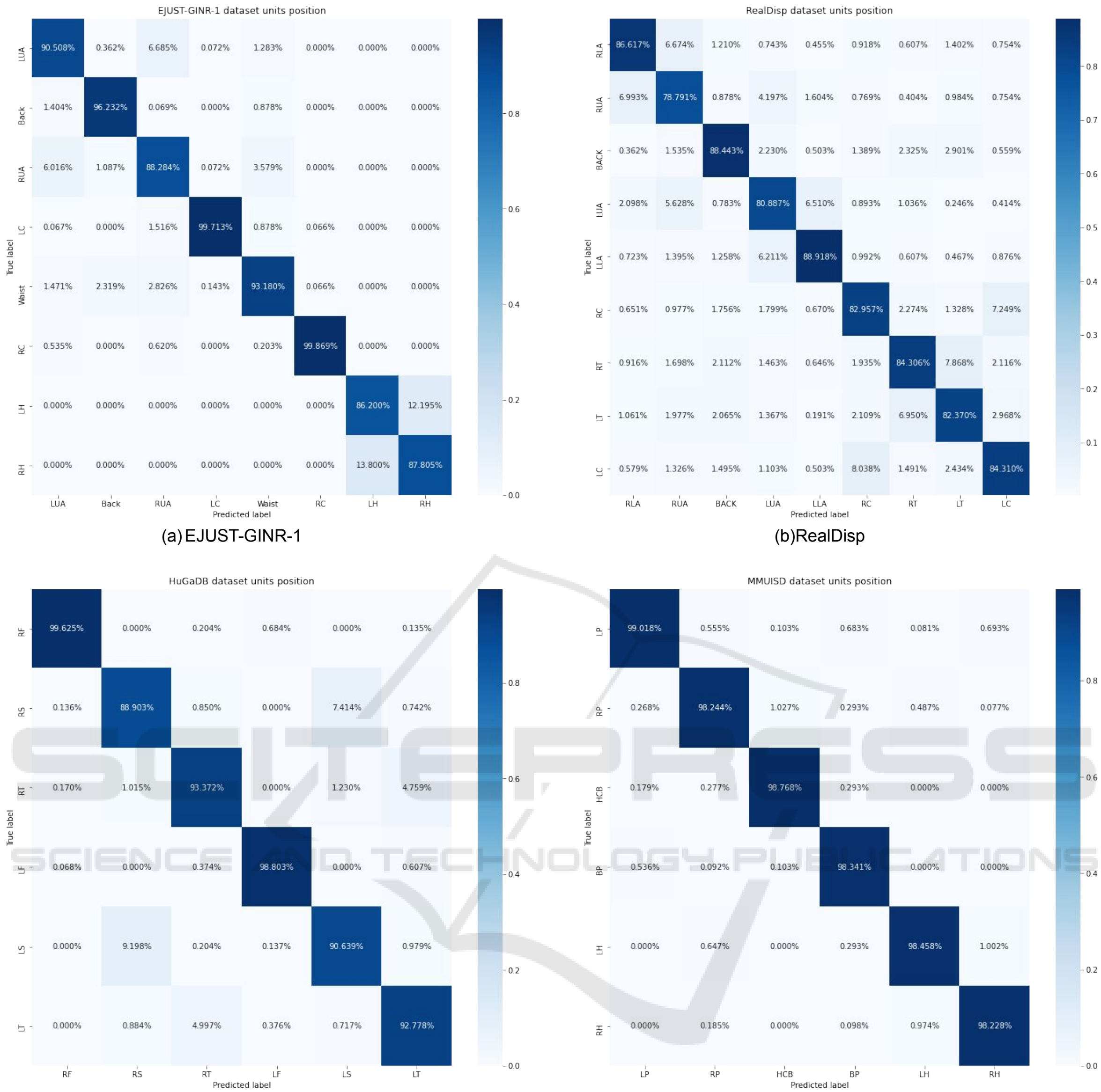
As we saw in Section 4.1.3 this dataset is mush different in the placement of their sensor units, as all of the 6 sensors are located on different places along the two legs, so we are inspecting how the model could differentiate between places that are very proximal. As we see in the confusion matrix Figure 3c, we can observe that RT and LT have some wrong cross predictions by about 4.997% for the RT and 4.759% for the LT. Also, for the Right Shin (RS) and Left Shin (LS) they cross-predict each other by 9.198%, for the RS and 7.414% for the LS. For the Left Foot (LF) and Right Foot (RF) there is nearly negligible conflict between them.

5.1.4 MMUSID

The MMUSID dataset is totally different and include locations for the sensors the other three datasets did not cover, also it more mimics sensor placement in real-life(Permatasari et al., 2020) and as we see in Figure 2d. The sensors are carried mobile phones, in the left and right pockets (LP and RP), in the BackPack (BP), being hold in the two hands (LH and RH), and the last one has been in a hand carry bag (HCB). Those 6 locations are common places to put your phone in. Therefore, from the confusion matrix in Figure 3d we can clearly see that because of the distance found between locations of the sensors there is nearly no conflict found. However, we can see that the HCB has a little conflict with the RP by 1.027%. Also, the RH has little cross conflict with the LH by 1.002%.

5.2 Discussion

From the above results and observations, we can conclude that in the three datasets EJUST-GINR-1,



(a) EJUST-GINR-1 (b)RealDisp (c) HuGaDB (d) MMUSID

Figure 3: Confusion Matrices.

RealDisp and HuGaDB, there is high degree of confusion between the right and left body parts i.e. LUA and RUA, LLA and RLA , RS and LS, etc. Similarly, there is a high degree of confusion between the sensors on the same limb, for instance, the sensors on the RUA and RLA and LUA and LLA.

Hence, it is apparent one can use the readings from a sensor mounted on one side of the human body to infer the readings from the opposite side. Also, it shows that the difference between readings from proximate body parts are subtle and should not make an issue for a model trained on data from one of them. However, the data readings, in the MMUSID, from the right and left feet are unique, and separate models are required to for each side.

On the other hand, in the MMUSID dataset, we found that there is a false prediction in the place of the HCB sensor with the RP sensor, which indicates that nearly all the subjects carry their bags in the right hand which makes the data biased towards the right handed people only and this may give false predictions in the experiments done on this dataset.

Table 2: Classification report for Datasets.

Datasets	Units	Precision	Recall	F1-Score	Accuracy
EJUST-GINER-1	LUA	0.90508	0.91734	0.91117	92.86%
	Back	0.96232	0.97432	0.96828	
	RUA	0.88284	0.88958	0.88620	
	LC	0.99713	0.97407	0.98547	
	Waist	0.93180	0.93369	0.93275	
	RC	0.99869	0.98700	0.99281	
	LH	0.86200	0.87969	0.87075	
	RH	0.87805	0.86015	0.86901	
RealDisp	RLA	0.86617	0.86994	0.86805	84%
	RUA	0.78791	0.83141	0.80907	
	Back	0.88443	0.88506	0.88475	
	LUA	0.80887	0.82048	0.81464	
	LLA	0.88918	0.87701	0.88305	
	RC	0.82957	0.82937	0.82947	
	RT	0.84306	0.81188	0.82718	
	LT	0.82370	0.81449	0.81907	
	LC	0.84310	0.83337	0.83821	
HuGaDB	RF	0.99526	0.98984	0.99304	93.98%
	RS	0.88903	0.91019	0.89949	
	RT	0.93372	0.92804	0.93087	
	LF	0.98803	0.98938	0.98871	
	LS	0.90639	0.89236	0.89932	
	LT	0.92778	0.93029	0.92903	
MMUSID	LP	0.99018	0.97882	0.98447	98.49%
	RP	0.98244	0.97882	0.98447	
	HCB	0.98768	0.99175	0.98971	
	BP	0.98341	0.99213	0.98775	
	LH	0.98458	0.98139	0.98298	
	RH	0.98228	0.98837	0.98532	

6 CONCLUSIONS AND FUTURE WORK

In this work, we investigated the problem of detecting the location of an Inertial Measurement Unit (IMU) on the human body. The detection of the location of these devices accurately can have a huge impact on the accuracy of human activity recognition (HAR) and person identification. Therefore, we train a Random Forest Classifier on four different publicly available datasets separately and report the accuracy, precision, recall and F1-score on each one of them. Moreover, we show the confusion between the classification of each location and get some important insights. Our model achieved 98.82% accuracy on the MMUSID dataset which mimic real-life sensor placements, 93.68% accuracy on HuGaDB which incorporates 13 activities, 92.85% accuracy on EJUST-GINR-1 dataset and 83.86% accuracy on ReadlDisp dataset which incorporate 33 activities. It is important to notice that we train our model on the raw inertial data without doing any feature engineering.

In the future, we plan to extend this work to include sensor location determination from many other actions. From these we can see how different actions are dependent on the motion of different body parts, which can be used, for example, in treatment assessment for people with motion disabilities. Another line of research would be to map the signals streamed from a given sensor mounted on a specific place on the body to signals as if they were streamed from other body parts. This can be considered as a data augmentation that would extend the size of the dataset without actually recollecting data using physical sensors mounted on the target body parts.

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