Real-Time Human Activity Recognition Using Textile-Based Sensors

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Abstract. Real-time human activity recognition is a popular and challenging topic in sensor systems. Inertial measurement units, vision-based systems, and wearable sensor systems are mostly used for gathering motion data. However, each system has drawbacks such as drift error, illumination, occlusion, etc. Therefore, under certain circumstances, they are not efficient alone in activity estimation. To overcome this, hybrid sensor systems were used as an alternative approach in the last decade. In this study, a human activity recognition system is proposed using textile-based capacitive sensors. The aim of the system is to recognize the basic human actions in real-time such as walking, running, squatting, and standing. The sensor system proposed in this study is used to collect human activity data from the participants with different anthropometrics and create an activity recognition system. The performance of the machine learning models is tested on unseen activity data. The obtained results showed the effectiveness of our approach by achieving high accuracy up to 83.1% on selected human activities in real-time.

Keywords: Wearable capacitive sensors · Human activity recognition · Onset-offset detection

1 Introduction

The field of Human Activity Recognition (HAR) aims to monitor and model human behaviors and body kinematics. In daily life, humans perform different body motions to sustain life routines, to carry out duties or to meet their needs. A combination of the motions of different body parts represents a specific activity such as walking, running, jumping, sitting, standing, lying on the sofa, etc. where each body motion has some distinctive characteristics on the signal level. Last decade, the progress in wearable sensor technologies made it possible to

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collect useful data regarding body kinematics, muscle response, physical and neural changes that occur during the action. The estimation of these distinctive features is challenging, however capturing and modeling human movements provide utmost beneficial information for autonomous computer-aided proactive and personalized services. Therefore, in the last two decades, scientists have been intensively working on monitoring and modeling the body movements and utilizing the power of computers in terms of data processing, high computational capacities, and re-usability of activity data.

In HAR, vision-based sensors [1–3], embedded sensors such as accelerometer, gyroscope, magnetometer, etc., [4–6] and various body-mounted sensors [7–11] are popular technologies that are used to collect motion data. One of the most widely used sensors in HAR are the Inertial Measurement Unit sensors (IMUs). IMUs are capable of tracking kinematics of the user when they are attached to body joints. Although IMUs are rather low-cost, the localization of the IMUs is still a challenging task and IMUs are mostly prone to the drift problem that leads to cumulative error in sensing.

Currently, each sensor system has its limitations in terms of reliability, precision, power consumption and cost. There is no silver bullet for HAR yet and it has been a progressive field of research for the past two decades. With the development of the wearable textile-based sensors, motion data collection became more effective since they are manufactured from flexible and body conformal textile material. The body-fitted wearable sensors are good at capturing the activity pattern as they are worn directly on body joints. Textile based sensors are widely used in a number of applications including sports/recreation [12,13], elderly care [14,15], rehabilitation [16,17], gaming [18–21], and robotics [22,23] etc. Herein, low-cost textile-based sensors manufactured [24] for this study were used to establish a wearable HAR system. Stretchable wearable braces are used for sensor attachment and placement on knees. It is feasible to measure different body kinematics by attaching them to belts, wristbands, or elbows.

The textile-based sensors have embedded capacitive, resistive, optical and piezoelectric properties that are able to sense strain, pressure, touch, temperature, humidity [25,26]. In this study, the textile-based capacitive strain sensors are used that measure the capacitance variation depending on the elongation during lower limb motion for HAR system. We tested our prototype system on four different lower limb motion activities; walking, running, squatting, and standing. We initially chose these basic activities before moving on to more complex activities, since these activities have distinctive signal patterns. We collected activity data from multiple participants. Each participant wore these knee braces and performed 4 different activities. Finally, we evaluated the performance of our HAR system by using signal segmentation and machine learning methods.

2 Related Studies

Although IMUs are one of the most commonly used sensors, they are not sufficient alone in terms of the performance in HAR, and scientists use some other auxiliary sensors. Wu et al. [27], used a combination of wearable flexible sensor and accelerometer to recognize activities of elderly people during the rehabilitation period. Hu et al. [28] manufactured a sensor system using flexible fabrics and conductive yarns that is attachable to the knee joints. An electrogoniometer was used as a reference sensor to calibrate their system. They compared the motion capturing performance of their system with the VICON [29] motion capturing system and stated that their system is able to accurately detect knee joint movements both indoor and outdoor without hysteresis.

Another example for the sensor fusion in HAR is reported by Leier et al. [30] who developed fall detection and activity recognition system. They manufactured a smart wearable sensor for people working in challenging conditions to detect accidental situations and give feedback.

Beside the classical machine learning algorithms such as those Support Vector Machine (SVM) [31], Decision Tree (DT) [32], Random Forest (RF) [33], k-Nearest Neighbor (kNN) [34], etc., Nguyen et al. [35] investigated a new machine learning approach for human activity recognition. They used an ensemble algorithm based on voting technique. Their model was trained on two static datasets called Mobile Health (MHEALTH) [36] and University of Southern California-Human Activities Dataset (USC-HAD) [37].

Vu et al. [38] produced a flexible sensor by padding conductive ink that contains conductive carbon nanotubes to a spandex fabric to detect basic human motions. They attached their sensor to a commercial muscle pants to collect data from the upper thigh. They obtained best results in terms of recognition accuracy with RF algorithm.

Apart from offline learning approaches, Bhat et al. [39] developed a framework that performs online learning and inference in HAR. They used a combination of strain sensor and accelerometer. They also used a low-cost Internet of Things (IoT) device to test their system. The policy gradient algorithm achieved great performance in HAR.

The novelty of our proposed system is to provide a new textile-based sensor system in HAR. The capacitive properties of the sensors are feasible to mimic human motions when they are attached to body joints. In this study, we tested the performance of our HAR system in terms of the accuracy and speed of activity classification in real-time.

3 Activity Recognition System Using Textile-Based Sensors

In this section, the infrastructure of the proposed human activity recognition system is introduced as illustrated in the flow diagram of Fig. 1: 1) Data acquisition of basic human activities, 2) Preprocessing, 3) Feature extraction, and 4) Classification.

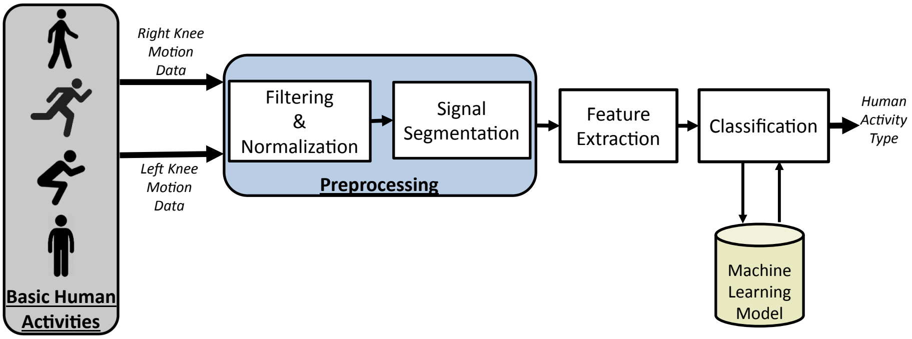


Fig. 1. Flow diagram of the proposed HAR system

3.1 Data Acquisition System

Textile-Based Capacitive Sensor. The sensor system used in this study is manufactured using low-cost textile materials with capacitive properties [24,40]. The sensors can be mounted to apparel pieces such as knee braces to sense the motion kinematics. The capacitive strain sensors consist of two pieces of knitted conductive fabrics and a silicone insulator between these fabrics. The capacitance value changes depending on the strain value of the fabric. The capacitance variation provides information about the movement when the sensors are attached to body joints such as knees. The structure of the capacitive sensor is illustrated in Fig. 2.

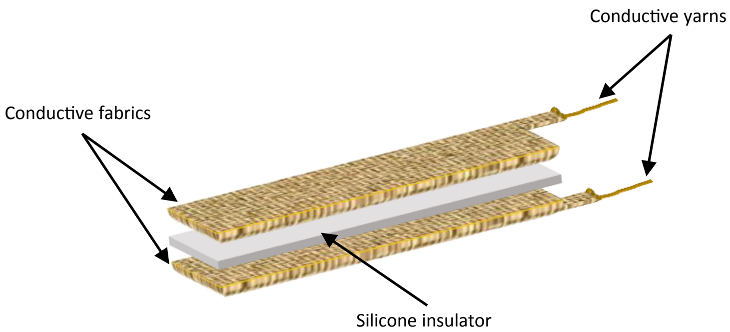


Fig. 2. Structure of the textile-based strain sensor

Design of the Knee Braces with Sensors. As legs are the most active body parts involved in many movements, we decided to track the knee joints. The knee joint movements yield information about the patterns of sports activities like walking, running, squatting, etc. One of the novelties of this study is producing a new wearable sensor to estimate human activities in real-time. Therefore, the sensors are affixed to braces worn on both knees throughout the data collection in the training and testing procedures (Fig. 3).

(a) frontal view (b) profile view

Fig. 3. Knee brace sensors

These sensors can easily be worn and taken off by the participants. In addition, they can be attached to fabrics on different body joints such as wristbands and elbows.

Design of the Hardware. Figure 4 shows a diagram of the data transmission process. The data transmission lines of the two knee sensors as shown in Fig. 3 are connected to a Transmitter Bluno (TB) module performing Bluetooth-based communication via a microcontroller.

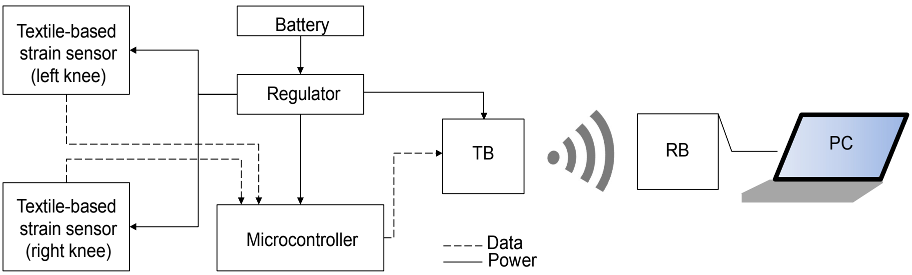


Fig. 4. Circuit diagram for data collection and transmission

A low-3.7V lipo battery is sufficient to power the TB module as well as the microcontroller and is attached to a small pocket case. The microcontroller connected to capacitive sensor measures the capacitance difference between the two ends of each sensor and transmits the values through conductive yarns to TB. These measurements are transferred to a Receiver Bluno (RB) module via Bluetooth simultaneously. The RB is attached to the USB port of the computer in our setup. The data collection process starts as soon as the Bluno connection is established. The data transfer rate is set to 50 Hz.

3.2 Preprocessing

Signal Filtering and Normalization. The TB transfers the following sensory data to the RB: 1) timestamp value indicating the exact time when data samples are read, and capacitance values that are read from 2) the Left Knee (LK) and 3) Right Knee (RK) at that time. A smoothing filter called Savitzky-Golay [41] is applied to the incoming data. Figure 5 displays the raw data belonging to different activity classes on the left column and, the filtered data on the right column.

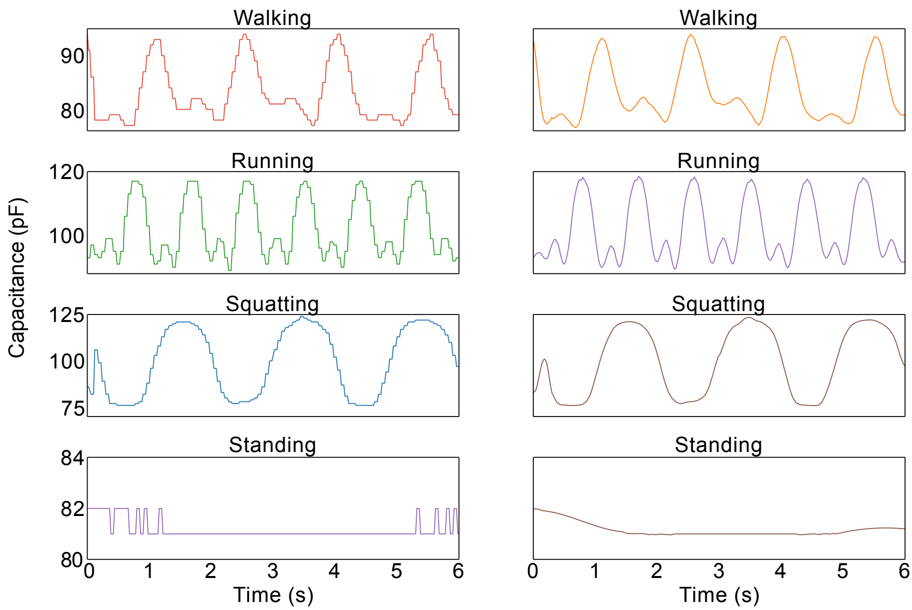


Fig. 5. Recorded signals of human activities before smoothing (left column) and after smoothing (right column)

In this study, we create different feature sets for obtaining the optimal HAR performance of our HAR system. We applied two different data normalization approaches by taking the ratio and the difference of raw sensor data retrieved from the right and left knees simultaneously. This approach is intended to improve the data integrity and make the features more robust, especially when one (or more) of the following changes: 1) the user of the braces, 2) the initial positioning of the braces at the knee of the user, and 3) the location of the braces while performing the activity.

Signal Segmentation. We applied two different types of signal segmentation methods based on 1) Sliding Window, 2) Onset-Offset Detection to investigate the effect of these two segmentation approaches on the performance of activity classification.

Sliding Window (SW) [42] is one of the most commonly used signal segmentation methods. We heuristically fixed the window and shifting size to 128 samples (2.56 s) and 64 samples (1.28 s), respectively. Therefore, two consecutive frames had 50% of data samples in common. We applied the First In First Out (FIFO) inventory valuation method.

Onset-Offset Detection (OOD) based segmentation approach is an adaptive segmentation technique. We applied an algorithm to extract each onset and offset from walking, running and squatting signals. A single onset-offset tuple is created using the samples starting with a left local minimum that is followed by a peak and then ending with the right local minimum.

3.3 Feature Extraction

In this section, we will explain the features extracted from the frames processed using the SW and OOD techniques, separately.

The SW technique provides a fixed-sized data frame with 128 samples in each time slot [43]. Figure 6 shows one instantaneous frame obtained from each activity. It is noteworthy to mention that during running, the participant takes almost twice as many steps as he/she takes during walking. During squat motion, the signals obtained from both knees are mostly amplitude-shifted versions of each other. During standing, the signals are more or less stationary. After normalizing the capacitance values retrieved from RK and LK sensors (i.e., the ratio and difference of RK and LK signals), we extracted the 8 statistical features given in Table 1.

Since OOD approach is an adaptive method for extracting frames, frame size is equal to the number of samples between the detected onset and offset and varies depending on the speed and step size of the activity, if any. A single frame captured arbitrarily between the detected onset and offset for each activity is illustrated in Fig. 7.

It is observed that walking and running activities have similar patterns; however, both the maximum and minimum values are larger in running, whereas the duration of running action is generally shorter. In the squat motion, the dynamic range between the maxima and minima regarding the capacitance change is larger due to the extended range of the knee activity. A frame for the standing action is not explicitly shown here, since it has no significant onset-offset difference. The statistical features in Table 1 are extracted from each consecutive frame obtained by applying OOD.

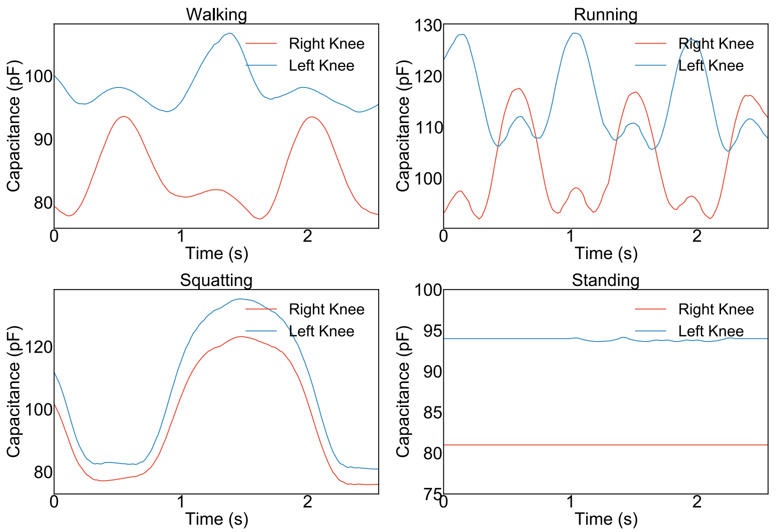


Fig. 6. Signals in one frame for each activity using shifting window method

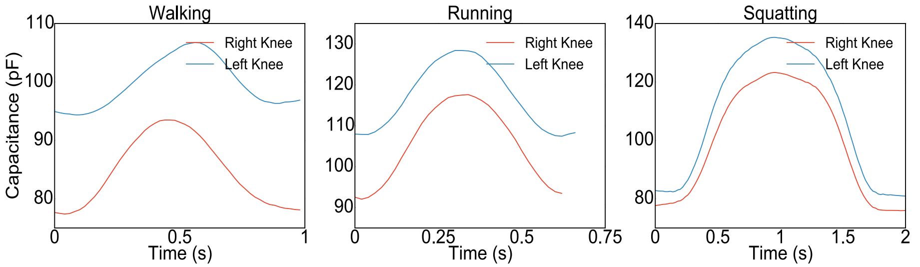


Fig. 7. Signals in one frame for each activity using onset offset detection method

As a consequence, each feature instance is labeled with action names and recorded in the feature set. The statistical features are used to model the distribution and tendency of data, because they provide distinctive properties for each activity class. Herein, the statistical features are the same for both segmentation methods.

3.4 Classification

Four different machine learning algorithms are proposed to be used in the framework of this paper. These algorithms are SVM, kNN, RF and DT. Each algorithm is trained using different parameters to create the corresponding models as given in Table 2. It is noteworthy to mention that the Radial Basis Function (RBF) [44] for SVM as a kernel achieved higher performance compared to other kernel functions.

Table 1. Features extracted from each frame.

Features	Definition
Mean	Central tendency of the data in one frame
Median	Value which divides the data in 2 equal parts
Min	Minimum value in a frame data
Max	Maximum value in a frame data
Standard deviation	Average distance between each quantity and mean
Kurtosis	Measure of whether the data has profusion of outliers or lack of outliers relative to a normal distribution
Skewness	Measure of the asymmetry of the probability distribution of a real-valued random variable
Quantiles	Points in a distribution that relate to the rank order of values in that distribution

Table 2. Hyperparameters of ML models

Model	Hyperparameter	Value
SVM-1	Kernel	RBF
	Gamma	0.01
	C	10
SVM-2	Kernel	RBF
	Gamma	"scale"
	C	1
DT	Criterion	"gini"
	Number of estimators	200
	Random state	0
kNN	Number of neighbors	5
	Leaf size	20
	Weights	"uniform"
RF	Criterion	"gini"
	Number of estimators	100
	Random state	0

4 Experiments

4.1 Experimental Framework

In this study, we used a specific sports activities dataset to compare the effect of two signal segmentation methods in classification. We investigated the performances of five different machine learning models and finally perform a real-time HAR. Firstly, we collected activity data from the participants using the knee brace sensors presented in the Sect. 3.1. Participants between the age of 21 to

30 and were assessed. Body weight and height of participants ranged from 62 to 75 kg and 168 to 178 cm, respectively. Each participant wears the braces and performs four different sports activities in different time slots. An experimenter checks the connection between the sensor and the computer to ensure that there is no interruption or distortion during the recording.

A PC with the following features; Intel Core i5 2.90 GHz with 8 GB RAM was used. On the PC side, all implementations involving signal processing, feature extraction, and classification were carried out using Python 3.7 platform.

4.2 Dataset

Our training and test data were collected from 3 participants with different anthropometrics in different sessions. The training data set include 36 min long data (12 min for each participant consisting of three minutes for each activity). The total number of data samples collected for the training process is 108.000 ($36 \times 60\,\text{s} \times 50\,\text{Hz}$). The testing data include 12 min long data (4 min for each participant consisting of one minute for each activity). The size of testing data is about 36.000 ($12 \times 60\,\text{s} \times 50\,\text{Hz}$).

4.3 Evaluation Criteria

Each machine learning model (i.e., SVM-1, SVM-2, DT, kNN, RF) is trained with the training set and tested with the test data. One of the main purposes of this study is to inspect the effects of two signal segmentation methods not only on the classification accuracy, but also on the response time considering the real-time constraints. Therefore, we evaluated the performance of each algorithm by using the 10-fold cross-validation method in terms of classification accuracy (Acc) and execution time (ET [s]) in an offline manner. In the real-time HAR system, however, we selected the system with the model showing the optimal performance.

5 Results

To demonstrate the importance of the features extraction in the offline tests, we compared the performance of the proposed system using feature vectors with the selected eight Statistical Features (w. SF) and without the statistical features (wo. SF), i.e. all samples in the frame (e.g., 128 samples) were used in the feature vector. In each experiment, we used the same classifiers with the same parameters.

Table 3 shows the classification results obtained using SW-based segmentation. This table is used to investigate the performance of different combinations of the signal processing pipeline including 1) Single sensor on one knee, 2) Two sensors without normalization, 3) Two sensors normalized by their signal ratio and, 4) Two sensors normalized by their signal difference.

Table 3. Results of classification using SW-based segmentation

Feature sets	MODELS									
	SVM-1		SVM-2		DT		kNN		RF	
	Acc	ET[s]	Acc	ET[s]	Acc	ET[s]	Acc	ET[s]	Acc	ET[s]
Single sensor (wo. SF)	0.399	15.00	0.661	5.80	0.717	4.08	**0.803**	**1.01**	0.762	28.89
Single sensor (w. SF)	0.771	1.95	0.515	1.68	**0.796**	0.26	0.786	**0.16**	0.785	8.21
Two sensors without normalization (wo. SF)	0.367	30.79	0.643	11.80	0.73	8.69	0.767	**2.52**	**0.772**	41.89
Two sensors without normalization (w. SF)	0.782	3.51	0.648	2.24	**0.831**	0.52	0.773	**0.28**	0.827	12.24
Two sensors normalized by ratio (wo. SF)	0.464	9.82	0.615	8.52	0.703	6.90	0.745	**1.94**	**0.754**	32.46
Two sensors normalized by ratio (w. SF)	0.495	1.45	0.611	0.98	0.751	0.14	0.682	**0.13**	**0.762**	7.16
Two sensors normalized by difference (wo. SF)	0.376	14.42	0.585	5.95	0.683	3.77	0.735	**1.11**	**0.752**	26.14
Two sensors normalized by difference (w. SF)	0.745	1.33	0.683	1.11	0.742	0.21	0.749	**0.14**	**0.76**	6.97

Overall results show that RF model achieved the highest accuracy on most of the feature sets. However, the highest accuracy is obtained by DT model with a value of 83.1% using two sensors without normalization and with statistical features. Although RF has the best overall performance in terms of classification accuracy, it is the laziest model in terms of ET. Herein, kNN proves to be the fastest model. However, DT can be chosen as the ideal model for our real-time HAR system with an acceptable processing latency. In addition, the results indicate that the SF have characteristic properties helping in the improvement of the classification accuracies in most of the classification models. It is also observed that the proposed normalization scheme by using neither ratio nor difference of the two sensor signals have contributed to an improvement in terms of accuracy.

In Table 4 the classification results of the onset-offset detection based segmentation approach is given. The best ET (0.20 s) is observed using kNN model. Herein, we omit the onset-offset dataset (wo. SF) since each detected onset-offset frame has a different number of samples and doesn't have a regular shape.

The detailed classification performance in terms of accuracy, precision, recall and F1-score for the DT model using SW-based segmentation and for the RF

Table 4. Results of classification using OOD-based segmentation

Feature sets	SVM-1		SVM-2		DT		kNN		RF	
	Acc	ET [s]	Acc	ET [s]	Acc	ET [s]	Acc	ET [s]	Acc	ET [s]
Single sensor (w. SF)	0.782	3.65	0.473	2.94	0.801	0.34	0.758	**0.20**	**0.812**	9.48

model using OOD-based segmentation results are examined in Tables 5 and 6, respectively.

Inspecting the precision and recall values of the RF and DT algorithms for both segmentation approaches, we obtained similar results. Although these results show that RF is well-suited at classifying different types of sports activities, it is not an adequate model for real-time systems. Furthermore, the highest F1-Score is obtained by using the DT model using two sensors without normalization and SW-based segmentation.

The Confusion Matrices (CM) for the DT model using SW-based segmentation and for the RF model using OOD-based segmentation showing highest accuracy results are examined in Figs. 8a and b, respectively.

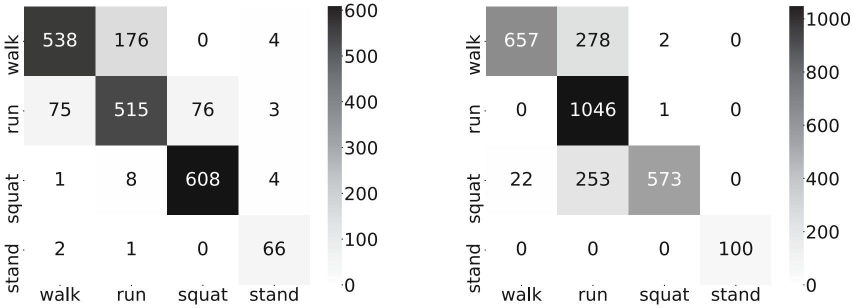
As can be clearly seen, the HAR models are more prone to misclassification between the human activities of walking and running. Besides, in OOD based classification, the models mostly confuse the activity pairs of walking and running, and running and squatting. Another important aspect to emphasize is that the number of instances in the standing activity are relatively less than other activities. Considering the performance of the recognition system is quite excellent for standing behaviour, a balanced data set after the segmentation having equal number of instances in each class would have drastically improved classification performance compared to what we have demonstrated here.

Table 5. Classification performance of different models using two sensors without normalization and SW-based segmentation

Model	Accuracy	Precision	Recall	F1-score
SVM-1	0.78	0.86	0.78	0.79
SVM-2	0.642	0.72	0.64	0.61
DT	**0.831**	0.83	0.83	0.83
kNN	0.773	0.84	0.77	0.78
RF	0.827	0.83	0.83	0.82

Table 6. Classification performance of different models using single sensor with OOD-based segmentation

Model	Accuracy	Precision	Recall	F1-score
SVM-1	0.782	0.84	0.75	0.75
SVM-2	0.473	0.53	0.48	0.40
DT	0.801	0.86	0.81	0.80
kNN	0.758	0.80	0.73	0.73
RF	**0.812**	0.87	0.81	0.81



(a) DT Model using SW segmentation (b) RF Model using OOD segmentation

Fig. 8. Confusion matrices of different HAR models

6 Conclusion

In this study, a novel approach is applied using textile-based knee sensors to recognize specific human activities, such as walking, running, squatting, and standing. These sensors have capacitive properties and are able to measure capacitance variation during the movement. We attached these sensors to knee braces to accurately measure the variations. We implemented two different signal segmentation algorithms, i.e. the sliding-window method and onset-offset detection method before statistical features were extracted. Using different classifiers, such as SVM, kNN, RF, DT, we evaluated the proposed system using performance criteria, such as classification accuracy and execution time. The overall classification results show that although RF attained the highest accuracy, it is the slowest model, thus not sufficient for our real-time HAR system. Therefore, DT model showing similar accuracy, but drastically improved execution speed is ideally recommended for HAR.

Due to Covid-19, we conducted this study with a limited size dataset. The classification accuracy also depends on the size of data. We believe that a higher accuracy will be obtained in a more balanced data set. In the future, we plan to improve our experimental setup and collect more activity data from multiple participants. Besides, only knee bracer sensors are used in this study. We aim to improve our sensor framework by attaching new sensors to full pants instead of knee braces. Our ultimate goal is to design a textile-based sensor that can be worn on the whole body. Moreover, in the next research, we will investigate the contribution of auxiliary sensors such as smartphone IMUs on the performance of the HAR system.

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