Continuous Human Activity Detection Using Multiple Smart Wearable Devices in IoT Environments

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Summary
Recent improvements on the quality, fidelity and availability of biometric data have led to effective human physical activity detection (HPAD) in real time which adds significant value to applications such as human behavior identification, healthcare monitoring, and user authentication. Current approaches usually use machine-learning techniques for human physical activity recognition based on the data collected from wearable accelerometer sensor from a single wearable smart device on the user. However, collecting data from a single wearable smart device may not provide the complete user activity data as it is usually attached to only single part of the user's body. In addition, in case of the absence of the single sensor, then no data can be collected. Hence, in this paper, a continuous HPAD will be presented to effectively perform user activity detection with mobile service infrastructure using multiple wearable smart devices, namely smartphone and smartwatch placed in various locations on user's body for more accurate HPAD. A case study on a comprehensive dataset of classified human physical activities with our HAPD approach shows substantial improvement in HPAD accuracy.

Key words:
Wearable sensors; biometric systems; biomedical monitoring; low-cost health care

1. Introduction

Continuous human activity detection is increasingly gaining importance in various applications, such as human behavior identification, healthcare monitoring, and user authentication. Human activities are very broad, some are primarily of physical nature, such as walking, running, sitting, and resting, and others are primarily mental or intellectual nature, such as participating in a meeting, thinking, and reading. Current human physical activity detection (HPAD) approaches can be categorized into three types: video sensor based, floor sensor based, and wearable sensor based [1,2]. Video sensor based HPAD approaches collect the user's related physical activity data from video sensors, floor sensor based HPAD approaches collect data from sensors embedded in the floor, and wearable sensor based HPAD approaches collects the data from sensors attached to the user's body. Among these three types of approaches, the wearable sensor based HPAD approach is considered most flexible, reliable and effective since the HPAD data can be collected without restricting the user's location or requiring the user to perform physical activity on a designated floor area. A wearable sensor based HPAD detection approach can monitor and collect the HPAD data using common smart wearable devices on the user anywhere and anytime. Due to the pervasiveness of wearable sensors and IoT equipment, people can wear more than one smart devices to assist their daily life [3]. Thus, this allows researchers to investigate the possibilities of utilizing multiple wearable devices for the sake of improving the accuracy of HPAD. Existing wearable sensor based HPAD approaches [4-9] have the following shortcomings: First, generally allow only predefined locations on the user's body for placing the wearable sensors. This can limit the user experience and also prevent the usage of biometric data from other parts of the user's body which can provide invaluable information. Second, do not incorporate the orientation of the accelerometer sensor in the HPAD. Third, yield relatively low HPAD accuracy due to the use of only one accelerometer sensor. That said, we believe the combination of multiple sensors can lead to better accuracy. These drawbacks can prevent us from fully exploit the advantages of wearable devices. To address these limitations, in this paper, we will present an efficient and effective continuous HPAD service to the user through mobile IoT platforms.

Our HPAD approach will be wearable sensor based and has much better accuracy rates than existing approaches [4-9] for HPAD. We will use two types of most common wearable smart devices, smartphone and smartwatch, to provide HPAD mobile service to users. Each of these devices contains multiple sensors to capture and record the user's human physical activity data. However, only the accelerometer sensors' data from smartphone and smartwatch will be used in our approach. An efficient fusion process will be used for merging the accelerometers' data for HPAD. A case study to illustrate our approach

Manuscript received February 5, 2021
Manuscript revised February 20, 2021
https://doi.org/10.22937/IJCSNS.2021.21.2.1.26

using a comprehensive dataset with classified human physical activities will be presented.

The organization of this paper is as follows: Besides the introduction section, the current state of the art of this area will be presented in Section 2, and our overall approach will be presented in Section 3. The fusion process for merging the preprocessed outputs from the accelerators is discussed in Section 4. In Section 5 the feature extraction from the fused dataset is presented. A case study based on a comprehensive dataset of classified human physical activities is presented to illustrate approach in Section 6. In Section 7, we will present our conclusion and the future work in this area.

2. Current State of The Art

As mentioned before, existing approaches to HPAD [4-10] use only one accelerometer sensor which limits the scope and quality of HPAD and their applications. In [4], a comprehensive context recognizer capable of recognizing ambulatory and transportation related activities, which include walking, jogging, standing, and riding a bus using accelerometer, microphone, and GPS sensors. This approach only uses sensors data from a smartphone. Furthermore, this approach uses GPS signal and the microphone in the smartphone, which increases the smartphone power consumption rate.

In [5], an approach to HPAD using an Android phone was presented. The location of the smartphone is fixed on the user's body (trouser pocket) during the data collection. This approach used a decision tree for classification of six activities which are walking, jogging, ascending stairs, descending stairs, sitting, and standing. However, this approach cannot be applied to the problem of varying sensors locations.

In [6] an algorithm based on a hidden Markov model to HPAD activities from acceleration signals collected by a single waist-mounted tri-axial accelerometer in a garment. This approach concatenates three channels of acceleration signals from each activity class as feature vectors to construct a hidden Markov model to recognize different daily activities including walking, standing, running, jumping, sitting, and falling. The experiment data was collected from 13 users and resulted in collecting 492 samples. This approach has serious limitation since it is based on data from one sensor which does not much with our objective to obtain global information about the body.

The HPAD approach presented in [8] used the acceleration data collected from the waist using a triaxial accelerometer CDXL04M3 marketed by Crossbow Technologies. Only few features, the mean, energy, standard derivation, and the correlation, were extracted for standing, walking, running, climbing upstairs, climbing downstairs, sitting, vacuuming and brushing teeth activities. The machine learning classifiers that were used include: Naive Bayes, kNN, SVM, and Decision tree which showed low HPAD accuracy.

The HPDA approach presented in [5] used the acceleration data collected from 29 users using an Android smartphone placed in the user's pocket. This approach was proposed to detect six activities: walking, jogging, going upstairs, and downstairs, sitting, and standing. This approach used three learning algorithms: Multilayer Perceptron, Logistic Regression, and J48. However, in this paper, the device's orientation was not being considered which can affect the collected acceleration data and may reduce the detection accuracy.

In [10], a multi-model sensor board (MSB) containing an accelerometer sensor, along with audio and barometric sensor was used to gather the user's activity data for HPAD. This approach proposed to recognize the following eight daily activities: sitting, standing, walking, walking down and upstairs, riding elevator up and down, and brushing teeth. Twelve users were involved during the data collection. However, in the recent implementation, the using of the audio as sensor modality is eliminated to be used for HPAD [11].

In [12] an approach to HPAD using a smartphone and simulated smartwatch was presented. This approach used three different sensors which are accelerometer, gyroscope, and magnetometer to collect data from ten participants from five different positions which are right and left pocket, waist, wrist, and right upper-arm. Different sets of features were extracted from the collected data to detect the following activities: walking, running, sitting, standing, jogging, biking, walking upstairs and walking downstairs. In [13] Ortiz et al. presented the Transition-Aware Human Activity Recognition (TAHAR) architecture for the recognition of physical activities which combines inertial sensors for capturing body motion, a machine learning algorithm for activity prediction and a filter of consecutive predictions for output refinement. They showed the usefulness of three human activity datasets with diverse groups of activities, number of sensors and number of participants on the success of body activities recognition using Support Vector Machine (SVM).

In [14] authors propose a novel deep neural network architecture for human activity recognition based on multiple sensor data. In [15] Ul-Hag at el. propose viable multimodal feature-level fusion. This approach utilizes data from multiple sensors, including RGB camera, depth sensor, and wearable inertial sensors. The proposed framework was tested on a publicly available multimodal human action dataset, called UTD-MHAD, which consists of 27 different human actions. Support Vector Machine (SVM) and K-nearest neighbor (KNN) classifiers were used for training and testing. The experimental results indicate that the proposed scheme achieves better recognition results as compared to the state of the art.

3. HPAD System Design

\indent In this section, we present the objective and the design of our approach and we elaborate on the data combination. In addition, we explain the feature extraction process.

3.1 Our Approach

The primary objective of our approach is to perform accurate HPAD with multiple sensory devices. The approach will have an improved HPAD accuracy due to the availability of rich user information which is obtained by fusing collected raw data from multiple locations of the user's body. Existing techniques to HPAD is commonly achieved either by measuring and processing gait cycles [16, 17] or based on window samples (non-cycles) [18, 19] of accelerometer data. In our approach we use a non-cycles-based representation because it does not require any additional processing and acquired inertial data can be framed into either overlapping or non-overlapping frames. The sliding window technique is used to scan the raw data (recorded data) and extract features from windows of Window-Length on short frame with fixed length. Our algorithm observes the accelerometer data in five second intervals/windows and extracts their corresponding features. We apply five second intervals/windows because it has been considered as sufficient period of time to observe and extract enough features [19].

The stepwise description of our approach as depicted in Figure 1 is summarized as follows:

Step 1) Collect the accelerometer data continuously from each smart wearable device used in our approach (only smartphone and smartwatch are used in our current approach).

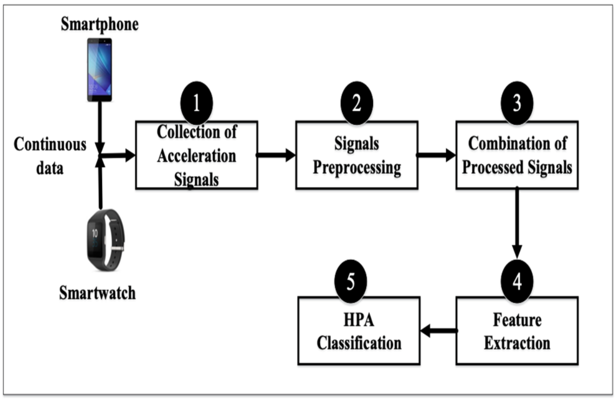

Figure 1: The process flow of our approach to continuous HPAD detection using multiple body-area devices in IoT.

Step 2) Remove the noise and normalize the collected accelerometer data, from each smart wearable device using the existing methods, such as those in [16]. Also, solve the problem of the device's orientation by computing the magnitude using Euclidean norm.

Step 3) Combine the normalized acceleration data from all smart wearable devices with appropriate weighting factors. The details will be presented in Section 4.

Step 4) Extract the relevant features of the human activities to be detected from the output of Step 3). The details of this step will be presented Section 5.

Step 5) Classify the output of Step 4) using a KNN classifier [20], which has been trained using a given dataset for the human activities to be detected.

As mentioned in Step 2), the collected raw accelerometer data needs to be processed for removing noise, deriving net acceleration signals, and removing corrupted data if any. Usually, the raw data will vary depending on how the devices are oriented on the body locations [21]. Therefore, to overcome this issue, we need to obtain a value that is independent of the device's orientation and derive a net acceleration independent of orientation by computing the magnitude of all three axes using Euclidean norm. For noise removing from the signals, we apply weighted moving average (WMA) filter to remove noise since it is quick and simple to implement [16]. The WMA filter takes a weighted average of a number of samples. In Step 5), we use the accelerometer dataset for HPAD obtained from Pervasive Systems Research Group [12]. This dataset contains acceleration data of ten participants and classified into different classes: walking, sitting, standing, running, biking, walking upstairs and walking downstairs. However, we only consider six classes: walking, sitting, standing, running, walking upstairs and walking downstairs which are the most common activities. This part will be described in Section 6.

3.2 Sensor Data Combination

This section demonstrates the third step in our approach. Most current approaches in the area of activity detection do not consider the combination of the sensors data for improving HPAD accuracy rates. Fused accelerometer sensor data from multiple sensors tend to be more precise than those based on a single measurement. This is because it can measure more complete and complex information about the user. Therefore, this encourages us to use the Central Limit Theorem [22] in our approach to perform sensor level fusion of the accelerometer axes data of smartphone and smartwatch, which is represented by X_C, Y_C, and Z_C. The Central limit theorem states that the mean (average) of a sufficiently large number of independent random variables, each with finite mean and variance, will be approximately normally distributed [10]. Therefore, we use it for the collected data which represents random variables whose distributions are not known. In our implementation, we apply the following steps:

- Uniformly sample the collected acceleration data X_A, Y_A, and Z_A from sensor set A and \$$X_B$, Y_B, and Z_B from sensor set B. Set A represents the data collected from devices A (smartphone) and set B represents the data collected from device B (smartwatch).
- Fuse the two sensor sets by selecting *n* number of samples from these two sets until we go over all the values in A and B.
- Average these samples and check the frequency and the representation of these new averaged samples.
- To obtain the new set C= X_C, Y_C, and Z_C , we combine the two sets by weighting their respective variances:
  - Let X_A, and X_B, denote two X axis sensors measurements with lower variances σ_1^2 and σ_2^2 , respectively.
  - Let Y_A, and Y_B, denote two Y axis sensors measurements with lower variances σ_1^2 and σ_2^2 , respectively.
  - Let Z_A, and Z_B, denote two Z axis sensors measurements with lower variances σ_1^2 and σ_2^2 , respectively.

Therefore, using the following equations 3, 4, and 5, we get our new fused data set.

$$x_c = \frac{1}{\sigma_1^{-2} + \sigma_2^{-2}}\left(\frac{x_A}{\sigma_1^2} + \frac{x_B}{\sigma_2^2}\right)$$

$$y_c = \frac{1}{\sigma_1^{-2} + \sigma_2^{-2}}\left(\frac{y_A}{\sigma_1^2} + \frac{y_B}{\sigma_2^2}\right)$$

$$z_c = \frac{1}{\sigma_1^{-2} + \sigma_2^{-2}}\left(\frac{z_A}{\sigma_1^2} + \frac{z_B}{\sigma_2^2}\right)$$

The size of the samples (the value of the number of sample (n)) is not restricted in our implementation since we are later, during the feature extraction step, dealing with the sliding windows of five seconds.

3.3 Feature Extraction

In this section, which presents step 4 of our approach, we will discuss how to extract the relevant features from the normalized and fused dataset. As mentioned above there are two possible ways to extract the activity's features from the captured signals which are either cycle-based or non-cycle-based [19]. In this paper we use a non-cycle-based representation where features are extracted from the times-series data from a selected time window. It does not require any additional processing since acquired inertial data can be framed into either overlapping or non-overlapping frames. In this approach the non-overlapping is used because it is not computationally expensive. The sliding window technique is used to scan the raw data (recorded data) and extract features from windows of Window-Length. The five second windows are used for feature extraction, which is considered not too short and not too long [23, 24]. Each window has no overlap applied on the 3-D accelerometer signals, which means that the original signal of length l is split into segments of length t. The following are the statistical features calculated for the acceleration signals [23-25] and each of them provides sufficient information for discriminating the users' HPAs [24].

1. Mean value of the magnitude data

$$\mu = \frac{1}{n}\sum_{i=1}^{n} \text{Xi}, \qquad \text{where } \text{X} = x_1, x_2, \dots, x_n$$

2. Maximum value: is the maximum value of $\text{X} = x_1, x_2, \dots, x_n$

$$MAX_x = \max(x)$$

3. Minimum value: is the minimum value of $\text{X} = x_1, x_2, \dots, x_n$

$$MIN_x = \min(x)$$

4. Root mean squared acceleration (RMS)

$$X_{rms} = \sqrt{\frac{x_1^2 + x_2^2 + \cdots + x_n^2}{n}}$$

5. Standard Deviation
6. Average Standard Deviation
7. The sum of height of frequency component below 5 Hz
8. Number of peaks in spectrum below 5 Hz

4. Evaluation

The dataset collected by Pervasive Systems Research Group was used for evaluating our approach. The dataset consists of the accelerometer, gyroscope, magnetometer, and linear acceleration sensor data from 10 users from different locations: waist, right pocket, left pocket, arm, and upper arm. However, we only used the acceleration data to perform our study. The activity data was collected while the participants were performing the following activities: walking, sitting, standing, running, jogging, walking upstairs and walking downstairs. The extracted features of each activity will be used to train a classifier to learn each individual's activities. The K-Nearest Neighbor classifier (KNN) which is provided by Weka as a class "IBk", was implemented since it is efficient in matching unknown patterns of data with a known pattern of data based on their euclidean distance metric. Furthermore, Random Forest, NaiveBayes, NBTree, and J48 were also implemented to benchmark our results. Each algorithm runs 10-fold cross validation for both individual devices and fused devices. The cross validation has been done using WEKA software. It splits the training and testing data by applying k-fold where k-1 for testing and the remaining for the training. Figure 2 presents the accuracy of four different positions combinations. The recall and precision of these four combinations are shown in Fig 3-10. Figure 11 shows the five algorithms and their detected accuracy values applied on the features extracted from smartphone placed in his right pocket, left pocket, right upper arm, and belt, and Figure 12 shows the found accuracy of a smartwatch placed on the wrist.

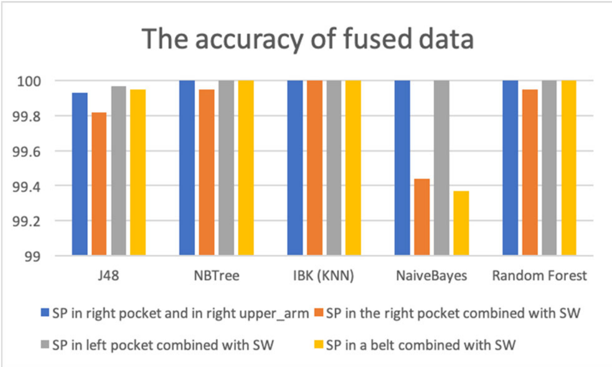

Figure 2: The accuracy of four different positions combinations.

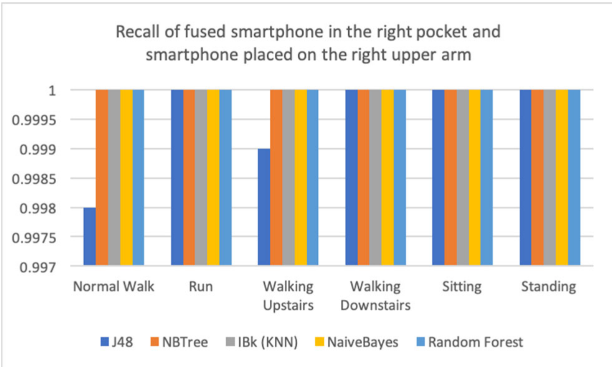

Figure 3: Recall of the fused smartphone in the right pocket and smartphone placed on the right upper arm.

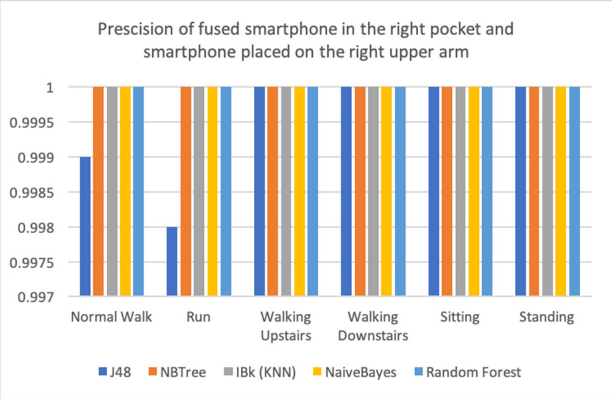

Figure 4: Precision of the fused smartphone in the right pocket and smartphone placed on the right upper arm

We apply two fusion techniques: 1) Multiple Devices Fusion, and 2) Single Device Results. In the first techniques, we merge the features extracted from different positions either from same device or different devices to recognize an action using a supervised machine learning approach. However, in the second technique we separately investigate data collected from different devices.

4.1 Fused Devices Results:

We fuse the smartphone (SP) accelerometer data from four positions of the body either with each other, two positions at a time, or with the accelerometer data from the smartwatch (SW). Figures 2-10 show the accuracy, recall, and precision results after the combinations. The smartphone is placed here in the right pocket, left pocket, right upper arm, and waist (belt) and the smartwatch on the right wrist.

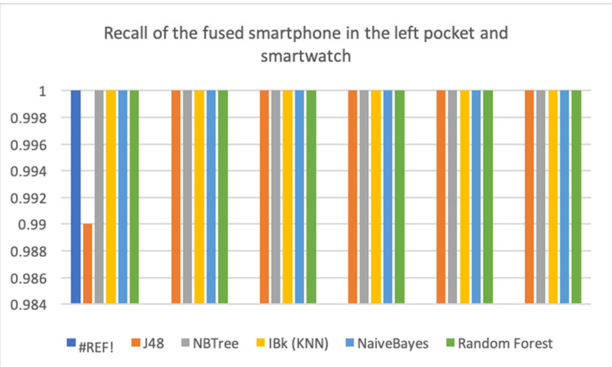

Figure 5: Recall of the fused smartphone in the left pocket and smartwatch

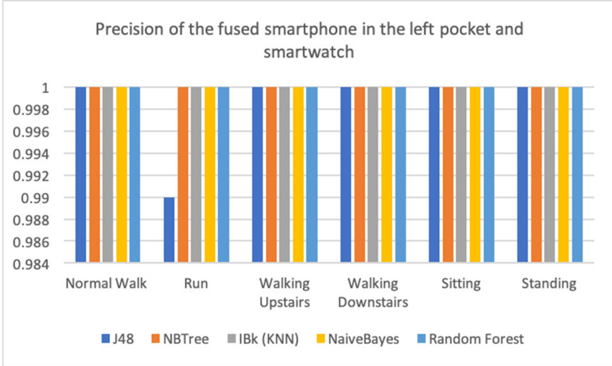

Figure 6: Precision of the fused smartphone in the left pocket and smartwatch

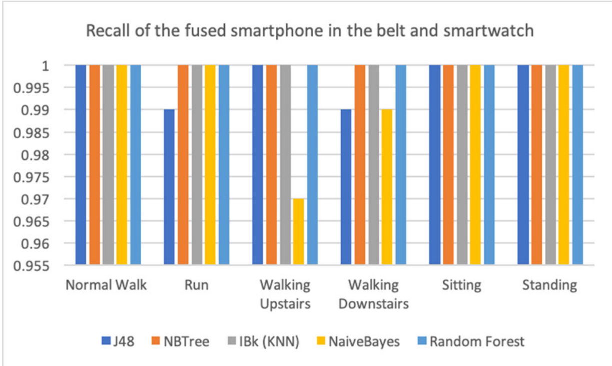

Figure 7: Recall of the fused smartphone in the belt and smartwatch

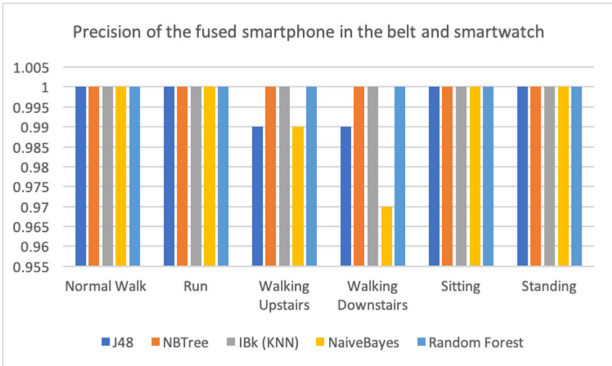

Figure 8: Precision of the fused smartphone in the belt and smartwatch

4.2 Single Device Results:

In this part, the smartphone and the smartwatch data were investigated separately. Figure 11, and 12 show the accuracy results of both devices. Based on the results obtained from this case study, we got much better accuracy rates than existing approaches [4-8] for HPAD. The existing approaches [4-8] achieved HPAD accuracy of 92.43%, 91.7%, 64%, 94.8%, 90%, and 90% respectively.

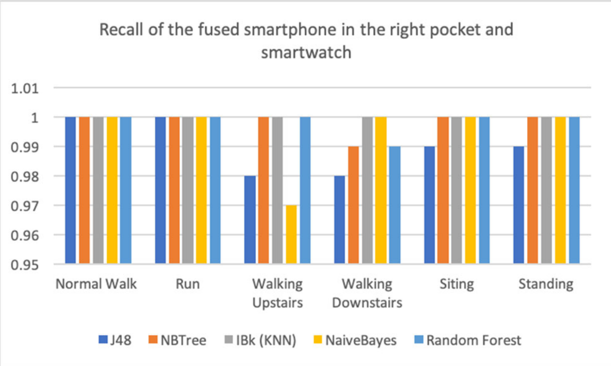

Figure 9: Recall of the fused smartphone in the right pocket and smartwatch

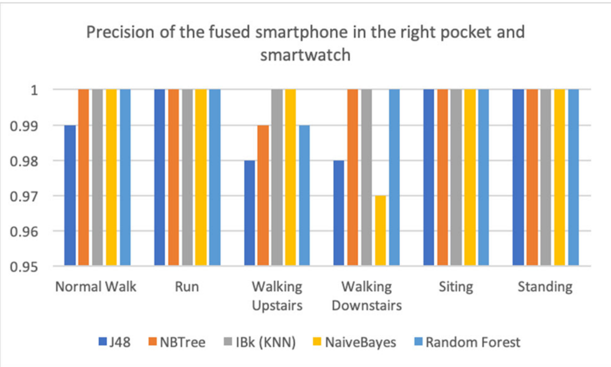

Figure 10: Precision of the fused smartphone in the right pocket and smartwatch

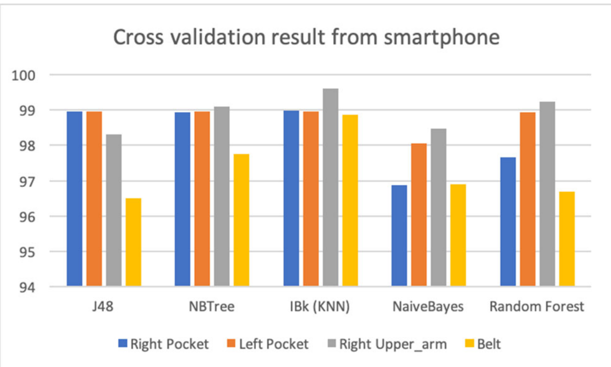

Figure 11: Cross validation result from smartwatch

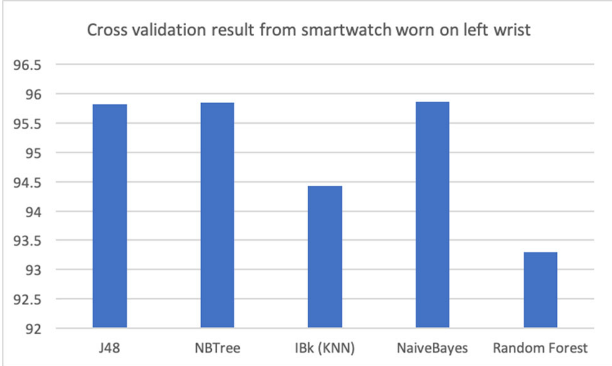

Figure 12: Cross validation result from smartphone

Our approach achieved HPAD accuracy of lowest of 99.37% when combining the two smart devices. Moreover, when applying our approach with the excluding of step 3 (combination of sensors data), we still achieved high accuracy when using single device. The lowest HPAD accuracy when using the smartphone was 97.51 and 93.29 when using the smartwatch.

5. Conclusion And Future Work

In this paper, a new HPAD approach is presented for detecting human activities using fused accelerometers' data from different locations of the user's body. Our approach has shown that the fusion of wearable sensors' data improves the accuracy of the HPAD. The effectiveness and efficiency of applications such as human behavior identification, healthcare monitoring, and continuous user authentication can be improved using continuous HPAD since it provides clear picture about the current status of the user. For example, our HPAD approach can support multimodal biometric user authentication techniques by selecting the appropriate biometric data streams for the fusion process which is required in multi-modal user authentication. Selecting the appropriate biometric data streams reduces the overhead by eliminating unnecessary computation on useless biometric data streams. In our future work, we plan to investigate other sources of biometrics for HPAD such as gyroscope, magnetometer, skin conductance, and heart rate.

6. Acknowledgement

This work was funded by the Deanship of Scientific Research (DSR), University of Jeddah, Jeddah, Saudi Arabia, under grant No. (UJ-02-102-DR). The author, therefore, acknowledges with thanks DSR, University of Jeddah, Jeddah, Saudi Arabia, technical and financial support.

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