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Monitoring Real-Time Personal Locomotion Behaviors Over Smart Indoor-Outdoor Environments via Body-Worn Sensors

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ABSTRACT The monitoring of human physical activities using wearable sensors, such as inertial-based sensors, plays a significant role in various current and potential applications. These applications include physical health tracking, surveillance systems, and robotic assistive technologies. Despite the wide range of applications, classification and recognition of human activities remains imprecise and this may contribute to unfavorable reactions and responses. To improve the recognition of human activities, we designed a dataset in which ten participants (five male and five female) performed 11 different activities wearing three body-worn inertial sensors in different locations on the body. Our model extracts data via a hierarchical feature-based technique. These features include time, wavelet, and time-frequency domains, respectively. Stochastic gradient descent (SGD) is then introduced to optimize selective features. The selected features with optimized patterns are further processed by multi-layered kernel sliding perceptron to develop adaptive learning for the classification of physical human activities. Our proposed model was experimentally evaluated and applied on three benchmark datasets: IM-WSHA, a self-annotated dataset, PAMAP2 dataset which is comprised of daily living activities, and an HuGaDB, a dataset which contains physical activities for aging people. The experimental results show that the proposed method achieves better results and outperforms others in terms of recognition accuracy, achieving an accuracy rate of 83.18%, 94.16%, and 92.50% respectively, when IM-WSHA, PAMAP2, and HuGaDB datasets are applied.

INDEX TERMS Body-worn sensors, kernel sliding perceptron, real-time personal locomotion behaviors (RPLB), stochastic gradient descent.

I. INTRODUCTION

In recent times, there has been an increasing demand to improve community health and safety by the use of body-worn sensor technologies. Physical activity monitoring via body-worn sensors enables carers and responders to track daily activities in order to sustain and enhance the quality of the individual and social lives of vulnerable people [1]. Fortunately, more affordances, functionalities and features are emerging with developments in multimodal fusion sensors. Body-worn inertial sensors such as accelerometers, gyroscopes, and magnetometers have gained wide research attention and encouraged the development of novel HAR applications [2]–[5]. These applications include e-health, rehabilitation, security surveillance, emergency services, wellbeing assistance, smart homes and biofeedback systems. Each of these applications requires continuous monitoring and tracking [6]–[10]. Applications like these provide vital access to information regarding the well-being of vulnerable elderly people and children by placing multiple body-worn

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sensors on various parts of the body. In e-healthcare, vital information about elderly people and patients is recorded. That data is transmitted in real-time via communication technologies to remote support services [11]. These sensors can also be used to track and monitor different aspects of motion. Tracking and monitoring the daily activities of elderly people and children can strengthen their security and personal confidence. In rehabilitation therapies, inertial-based body worn sensors provide continuous gait tracking which assists therapists working with the elderly in their efforts to achieve more efficient recovery [12]. Security surveillance systems can detect potentially dangerous and unusual events in surroundings and abruptly alert emergency response teams. Body-worn inertial sensors track, record and transmit a substantial amount of information on general health, dietary habits and physical activities which help monitor and secure the wearer's wellbeing [13]. Smart home-based systems provide continuous physical support and cognitive stimuli which aid the development of children and enhance their learning and functionality. Similarly, biofeedback therapy [14] works effectively with virtual reality (VR) based systems to measure body functions and to monitor changes in bodily functions like heart rate and blood pressure; such systems may also be useful in stress reduction techniques. Overall, the main goal of wearable inertial sensors is to provide real-time detection and precise recognition of activities and their effects via information which is acquired from the sensors.

Continuing advancements in an ever wider range of body-worn sensors are facilitating greater understanding of complex human patterns via the fusion of sensors like accelerometers, gyroscopes, and magnetometers which together extract vital information on human body movements in 3-dimensional space [15], [16]. For example, accelerometers measure variations in speed by continuously monitoring physical activities. Gyroscopes sense inertial forces and measure the rate of change in angular motion of body. Magnetometers measure relative changes in magnetic fields at specific locations and deliver compass heading information. In order to optimize the functionalities of such sensors they are fused together into single units called Inertial Measurement Units (IMUs). These inertial based body-worn sensors provide real-time monitoring of human activities. One specific activity can be performed differently by diverse individuals and groups. Many activities that are different in nature may be comprised of similar behaviors or gestures (e.g., eating and drinking). These characteristics make satisfactory classification results difficult to achieve.

This paper deals with the classification of routine daily tasks (walking, exercise, ironing, reading, etc.) via multi-fused body-worn inertial sensors that detect movement in 9 Degrees of Freedom (DoF). The system measures static postures and dynamic movements in three-dimensional space by detecting changes in body position, rotation, and orientation. The main focus of this paper is to improve detection and recognition accuracy while reducing the complexities of the systems required for the recognition of routine daily tasks. Our human locomotion recognition system involves five main steps: positioning of sensors, denoising of acquired data from sensors, feature selection, optimization, and classification. Initially, we placed three inertial sensors (MPU-9250) at different body locations, specifically, wrist, thigh, and chest. The acquired data is processed through different filtering techniques (i.e., Gaussian, moving average, and zero phase) to eliminate noise from the essential data. Then various techniques (i.e., time domain features, wavelet features, and time-frequency domain features) are adapted in order to extract features from the denoised data. Due to the high dimensionality of features, we optimize the extracted features with Stochastic Gradient Descent (SGD) in order to select the optimized features for further classification. Finally, a multi-layered kernel sliding perceptron algorithm is applied to the optimized feature vectors in order to recognize and classify human locomotion activities with significant accuracy. For performance evaluation, we applied the proposed model to our self-annotated dataset named IM-WSHA which is based on different patterns of human locomotion activities. We also applied our proposed model to two public benchmark datasets named Physical Activity Monitoring for Aging People (PAMAP2) and Human Gait Database (HuGaDB). The major contributions and highlights presented in this paper are as follows:

- Multi-scale feature approaches are adapted, namely, time domain, wavelet domain, and time-frequency domain features of rigorous motion data.
- A multimodal based body-worn inertial sensor platform is proposed in order to provide complete position, orientation, and rotational independency by converting inertial sensor readings from body to earth coordinate system.
- A novel multilayered kernel sliding perceptron methodology is applied in order to deal with the complex patterns of human locomotion activities and also to improve the recognition rate of all three datasets.
- A self-annotated IM-WSHA dataset is introduced in this research. This dataset is publicly available for future use as a standard benchmark and to facilitate other researchers in the field of body-worn sensor technologies.
- Furthermore, a detailed comparative analysis was done on our self-annotated dataset (IM-WSHA) along with two public benchmark datasets named PAMAP2 and HuGaDB for human locomotion activities. Experimental results show a superior recognition rate for the proposed model compared with other state-of-the-art-methods.

The remainder of the article is organized as follows. Section II briefly reviews other state-of-the-art methods. Section III addresses our proposed methodology of human locomotion based physical activities recognition. Section IV analyzes the experimental setup and provides the results of our proposed method on multiple datasets along with a comparison of state-of-the-art-methods. Finally, Section V reports insights gleaned from these experiments, plus future directions.

II. RELATED WORK

Various researchers have applied different techniques to recognize real-time personal locomotion behaviors using a diverse set of sensors such as inertial based body-worn sensors and vision sensors. This section presents a comprehensive report of background studies on vision sensor based real-time personal locomotion behavior (RPLB) analysis and inertial sensor based RPLB analysis.

A. VISION SENSOR-BASED RPLB ANALYSIS

In vision-based RPLB systems, many analysts have employed image and video sensor technologies from RGB cameras and RGB-D sensors which are mainly used in surveillance-based systems for the monitoring and recognition of 3D-movements and behaviors of humans in real-time scenarios. Ni *et al.* [17] designed a database for human locomotion activities recognition (going to bed, eating a meal, drinking water, etc.) via the fusion of depth and video sensors. They utilized Microsoft Kinect sensors to monitor human activities. They developed two feature representation methods (STIPs and MHIs) for the analysis of 12 different behaviors. Smart home-based monitoring with the help of camera-based systems is convenient for behavior monitoring, but, in outdoor environments these systems restrict the movement of the subject within the specific range of the camera-detectors.

In [18], Sharif *et al.* proposed a framework for a human behavior recognition system. Their proposed method involves two steps. Firstly, multiple human motion regions are identified using a uniform distribution-based fusion method and EM segmentation. Then, multi-fused features from the video sequences of motion regions from different datasets comprising of HOG, LBP, and Harlick methods are extracted. Then, novel joint entropy and Euclidean based methods are applied for feature selection along with the multi-class SVM algorithm to analyze personal locomotion behaviors in real-time. The proposed approach produces better results in recognition in small datasets. To make the proposed approach more robust, dataset size should be increased for both training and testing. In addition, the proposed approach struggles in different light conditions which effects the segmentation accuracy. Furthermore, occlusions are not considered in this research. Ji *et al.* [19] deals with the existing problems in the interaction recognition algorithms such as imprecise feature descriptors induced by incorrect segmentation of the human body. To deal with this problem, a multi-stage probability fusion method is proposed. However, this method does not deal with the intrinsic properties of the human interaction and it is only functional in classifying extreme behaviours including violent activities and abnormal occurrences.

Kong *et al.* [20] focused more on partial videos which involve incomplete actions. They proposed temporal dynamics of human interactions in which every object should be detected and recognized. But this approach requires all possible rules of human interaction activities to be predefined. In addition, all instances of each activity should be basic, e.g., hugging and hand shaking, and identically performed. In [21], Wang *et al.* proposed a probability-based graphical model for monitoring continuous human activity in real-time. They divided the model into two components (substructive transition and discriminative boundary). They intercept the problem of continuous activity segmentation and understanding. But these methods have been detected to work offline only.

Jalal *et al.* [22] introduced a camera based HAR system for detecting daily life-logs of elderly people in an indoor environment by exploiting multiple features including silhouettes and body joint features respectively. However, the proposed approach lacks complex datasets which involve human-to-human interactions and human-object interactions. In [23], Ince *et al.* proposed a biometric system based model to detect human motion in 3d space via different angle patterns between skeleton joints. In addition, this system adopts an RGB-depth camera which seems appropriate for security surveillance systems and in elderly care environments. However, there are limitations associated with the proposed approach. Firstly, false skeleton detections give rise to incorrect angle computations which lead to inaccurate classification.

B. RPLB SYSTEMS VIA BODY-WORN INERTIAL SENSORS

Recent advances in body-worn inertial sensors have been successfully implemented by researchers to non-invasively monitor personal locomotion behaviors. In pursuit of behaviour monitoring, researchers have used a fusion of sensors to find a more efficient way of analyzing the human gait and to improve living comfort. Xu *et al.* [24], proposed a body-worn sensor based RPLB system to extract multi-features from Hilbert-Huang Transform (HHT). In addition, they introduced an Empirical Mode Decomposition (EMD) based technique to split inertial signals into IMF components in order to detect and identify human activities. Furthermore, multiple features are derived from Hilbert-Huang Transform (HHT) and EMD to detect twelve human activities. Furthermore, in this paper the PAMAP2 dataset is utilized which involves null values and missing data fields due to the misplacement of the sensors. This paper lacks consideration of missing values which break the continuity of the motion data and which may reduce classification accuracy. Interpolation or statistical computations are required to deal with these issues. In [25], Feng *et al.* developed an ensemble method via the fusion of independent Random Forest classifiers to recognize RPLB using multiple body-worn inertial sensors. The enhanced predictive capabilities of the Random Forest algorithm delivered a best selection for the inertial sensor-based healthcare monitoring systems. However, their experimental approach with default parameters lacks an explanation as to why random forest attains higher accuracy than other classifiers.

Gupta and Dallas [26] developed a real-time based patient monitoring system via a single body-worn accelerometer in order to improve the recognition rate. They also introduced effective features to recognize transitional activities (sit to stand, stand to sit, and stand to kneel to stand). The features include mean and variance trend, windowed mean and variance difference. The proposed features further extracted the characteristics of the signals in the window. Furthermore, more features are evaluated to capture the correlation between the signals. However, the main limitation of this work is that only two subjects were utilized for data collection which makes the dataset limited in diverse environment. In [27], Chen *et al.* presented an ensemble of LSTM-RNNs model integrated with scene information to examine accelerometer and gyroscope sensor readings to yield position-aware methods in order to improve the recognition rate. However, their proposed approach was only evaluated against one dataset. Jing and Cheng [28] introduced a model for the recognition of human daily activities and fall detection via multiple body-worn inertial sensors. In addition, the whole system is evaluated against complete activity set consisting of periodic, static and sporadic actions. Features are extracted in both time and frequency domains. However, their proposed approach was only tested on a few subjects when detecting accident events.

In [29], Abidine *et al.* presented a modified weight SVM for detecting daily human living activities performed in a smart home environment. In addition, they tackled the several issues in the implementation of the HAR algorithms such as irrelevant sequence features and class imbalance in the training data. To handle these issues, they proposed a new scheme to recognize daily living activities in smart home environments. Their system is based on the combination of principal component analysis (PCA), weighted SVM, and linear discriminant analysis. Firstly, the training set is reduced by the extracted features from PCA and LDA to acquire the most significant features. Then, weighted SVM is utilized for each activity class to handle an imbalanced daily living activity dataset to improve the recognition rate. Their proposed approach was evaluated overall against machine learning strategies to improve recognition. However, with the help of deep-learning techniques, this system can be improved effectively. In [30], Tian *et al.* introduced the ensemble learning based model to recognize daily living activities. Three base classifiers and support vector machines (SVMs) are trained by multiple features to create an ensemble learning based system. In addition, an adaptive fusion method extracted multiple features to improve the accuracy of human daily activities. However, more sensor locations with unsupervised learning techniques must be adopted to improve the recognition rate.

Cillis *et al.* [31] adapted a pervasive solution for human gait patterns (walking, standing, ascending stairs, and descending stairs) using a body-worn inertial based accelerometer sensor. They proposed an algorithm to work consistently with long-term applications. Their proposed approach adopts limited descriptors to detect four different gait patterns along with the decision tree classifier. Initially, they extract features from both windows and a dynamic collection of windows. However, the experimental results show a high rate of accuracy in static activities but a significantly lower rate for dynamic activities (ascending and descending stairs). The low computational overhead of the system could work well for real-time applications in healthcare. In [32], Samuel *et al.* introduced a motion recognition method with the help of an sEMG sensor to control an upper-limb prosthesis and other rehabilitation devices. They utilized myoelectric pattern recognition techniques with the use of conventional time domain features. In addition, different machine learning classifiers have been analyzed to select efficient classifiers for consistent performance. Linear discriminant analysis was adopted to improve the performance. In, [33], Samuel *et al.* proposed three new time domain features to enhance the performance of electromyography (EMG) in arm movement classification. They extracted three new time domain features named summation of square root, the mean value of the square root, and the absolute value of the summation of the expth root from the filtered EMG dataset. Furthermore, LDA and ANN were employed for recognizing the arm motion patterns of the subject. Results obtained using this approach are better at classifying arm motion patterns.

III. PROPOSED SOLUTION FRAMEWORK

Our proposed RPLB system recognizes 9-DoF of human activities using three body-worn inertial sensors with 3-axis varied signal values from accelerometers, gyroscopes, and magnetometers. Initially, signals acquired from IMU sensors are refined through median filters by eliminating minimal saw-tooth waves emanating from sudden movements. Secondly, these denoised signals are categorized by a fixed-sliding window (50ms). After the denoising phase, maximum signal values are kept in order to produce effective feature components. Thirdly, we came up with multi-fused features from different domains comprising time, wavelet, and time-frequency domain features, scaled via codebook generation for relevant feature selection. Finally, in the body worn based RPLB classification module, a novel ensemble classifier of Stochastic Gradient Descent and Adagrad optimization with kernel sliding perceptron is implemented on the relevant feature sets to recognize personal locomotion behaviors in real-time. Figure 1 shows the flow system architecture of the proposed RPLB system.

A. SIGNAL ACQUISITION AND PRE-PROCESSING

During signal acquisition, we acquire data from three body worn IMUs for further analysis. IMUs are single units that integrate accelerometer, gyroscope, and magnetometer sensors. Abrupt changes in movement cause random noise in sensor values and affect the shape of the signal. In order to maintain the shape of the data, we process the noisy signal data with a third-order median filter, a non-linear static denoising method that deals with the rigorous motion of inertial data without losing relevant data. The moving average

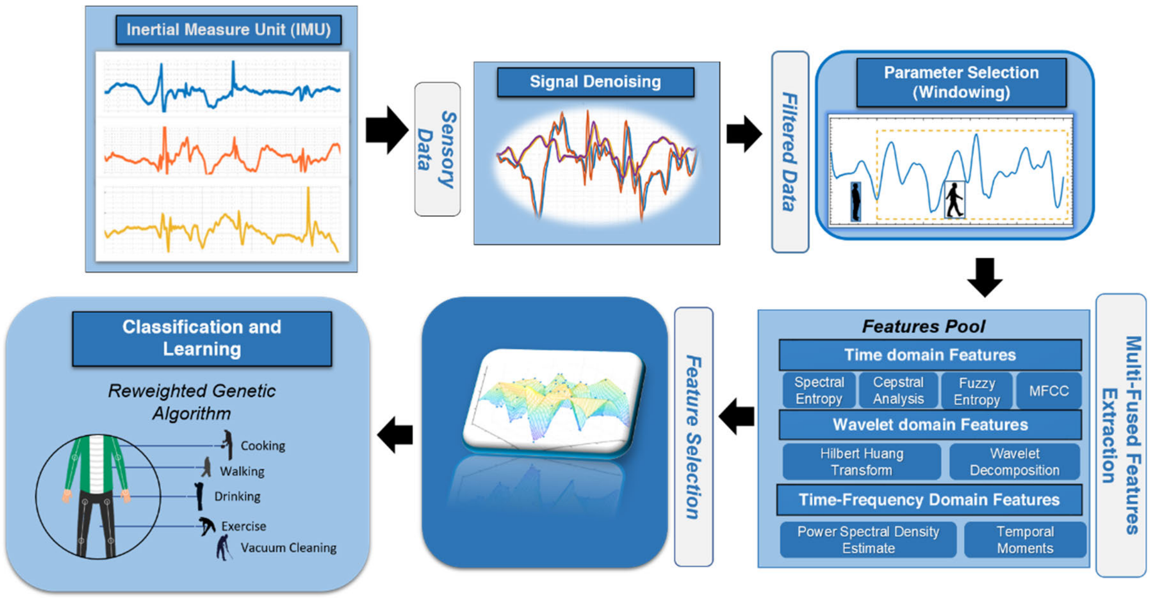


FIGURE 1. Flow architecture of the proposed RPLB system.

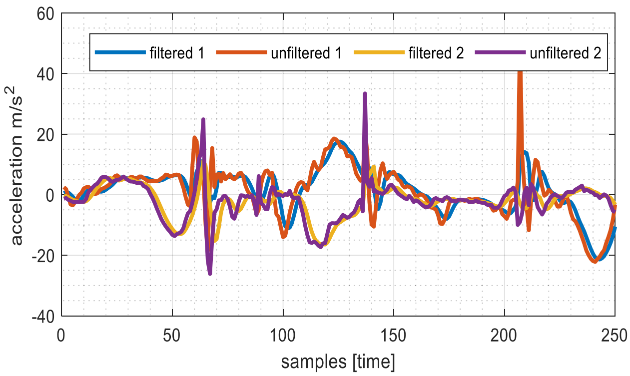


FIGURE 2. Signal Denoising. Inertial sensors with unprocessed (unfiltered) and processed (filtered) signals for correct walking activity via Gaussian filters on the IM-WSHA dataset.

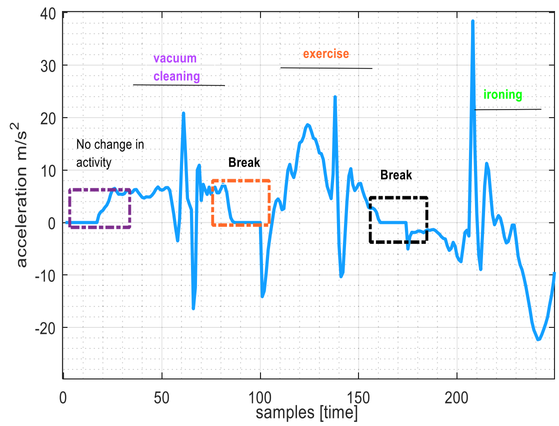


FIGURE 3. Window Selection for vacuum cleaning, exercise, and ironing activities from the IM-WSHA dataset.

filter analyzes the inertial signal data by taking the average of the initial subset. In addition, zero-phase digital filtering is used to deal with impermanent fluctuations in the signal, lowering the noise and preserving the important information in the signal. Furthermore, Gaussian filtering acts as a low pass filter which smoothens the signal but allows only smaller types of frequencies to pass through it.

Thus, we selected the third-order median filter based on these signal acquisitions compared to the rest of the filter's different noise types.

B. WINDOW SELECTION

We adapted a sliding window approach, which splits of the inertial-based sensor data into a fixed sizes for the analysis of human motion patterns [34]. This approach has been proven effective for recognizing static postures (e.g., lying, sitting) and dynamic locomotion activities (e.g., exercise, walking). In addition, the intricate motion patterns in PAMAP2 (ascending and descending stairs), HuGaDb (running and cycling) and IM-WSHA dataset (ironing and vacuum cleaning) activities involve breaks and jerks in indoor-outdoor environments. This behavioral pattern makes it difficult for the system to detect and recognize the behavior in minimal time. So, a window of 6 seconds was fixed to produce a better result.

C. MULTI-FUSED FEATURE EXTRACTION METHODS

In the feature extraction stage, we proposed a multi-fused feature model to get relevant features; it is comprised of three major domains including time, wavelet, time-frequency domain features.

Algorithm 1 Multi-Fused Inertial Signal (acc, gyro, mag) Features Extraction

Input: acc = acceleration data (x,y,z), gyro = gyroscope data (x,y,z), mag = magnetometer data (x,y,z),WS = window size and SR= Sampling Rate (100 Hz)
Output: feature vector for real-time personal locomotion behaviors (RPLB)
feature_vector ← []
  window_dimension ← AcquireWindow_dimension
  over_lap ← Acquirelap_time()
Method: RPLB(IMU(acc,gyro,mag))
  Multi-FusedVector ← []
  Filtered_Data ← Gaussian(acc,gyro,mag)
  Frame_Data(Filtered_Data, SR, WS)
While exit condition not true do
  Time Domain_features
  ← ExtractTimeFeatures(Frame_Data)
  TimeFrequencyDomain_features
  ←ExtractTFFeatures(Frame_Data)
  Wavelet_features
  ← ExtractWaveletFeatures(Frame_Data)
  Multi-FusedVector
  ← [Time, Time-Frequency, Wavelet_features]
end while
return Multi-FusedVector

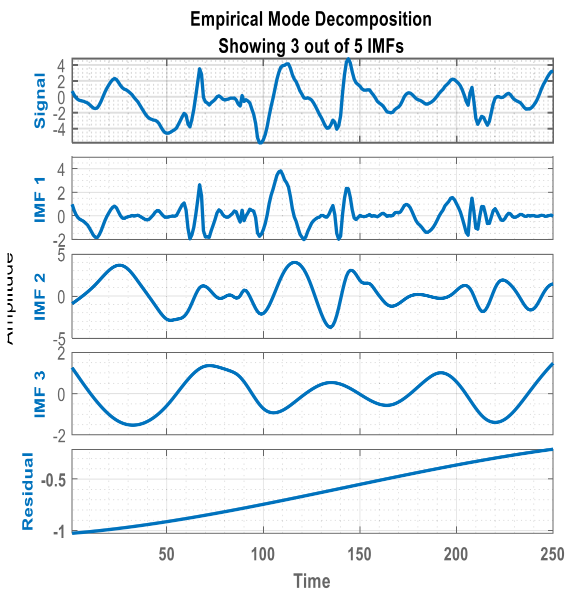


FIGURE 4. Empirical mode decomposition components from the inertial data.

1) HILBERT HUANG TRANSFORM

Hilbert Huang Transform (HHT) is considered to be very useful for non-linear and varied signal data [35]. In our case, three inertial sensors are attached to the human body. They deliver stream of time series data in real-time. In order to deal with specific activities such as exercising and walking which comprise repetitive patterns with dynamically varying amplitude and frequency, it is necessary to find temporal patterns for each activity. The data acquired from sensors are in time series and mostly non-linear in nature.

Initially, HHT decomposes the acquired time-series pattern into different repetitive components known as Intrinsic Mode Functions (IMF's) and the whole process is called Intrinsic Mode Decomposition (IMD). These multiple dynamic components give separate frequency bands and also catch Intra-wave Frequency Modulation. Furthermore, they can measure variations in Instantaneous Frequencies (IF). Finally, we can significantly analyze the invariability and characteristics of multiple activity data. The raw data R(t) can be calculated by:

$$R(t) = \sum_{j=1}^{n} c_j + r_n \tag{1}$$

where R(t) is the raw signal acquired from the inertial signal, c_j is the j^{th} IMF, and r_n is the remainder.

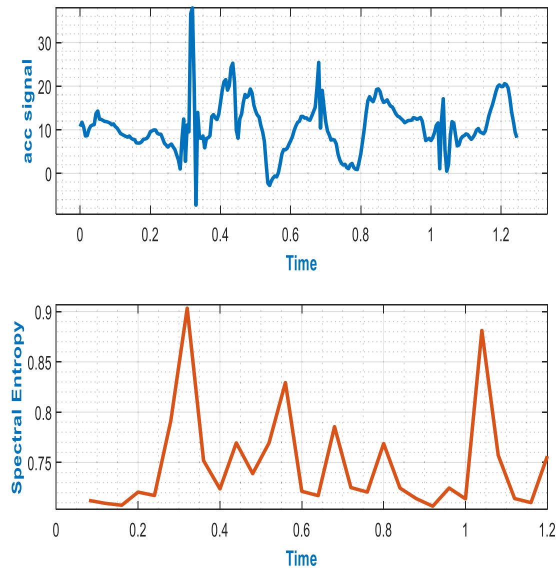


FIGURE 5. Spectral Entropy for the brushing hair signal pattern using the IM-WSHA dataset.

2) SPECTRAL ENTROPY

Spectral entropy (SE) [36] based on Shannon's Entropy theory measures randomness in the system which provides the system's complexity. The system's complexity delivers relevant information such as abrupt changes in body movement. That information is used to differentiate between different locomotion-based activities (walking and running, etc.). It also helps to calculate the inertial signal spectrum which provides a Power Spectrum to get relevant information about a specific activity. The features provided by spectral entropy are derived via the following steps:

- Initially, the Power Spectrum Ps of the acquired inertial signal is normalized and is called $Ps(f)$.

$$Q_s(f) = \frac{P_s(f)}{\sum_f P_s(f)} \tag{2}$$

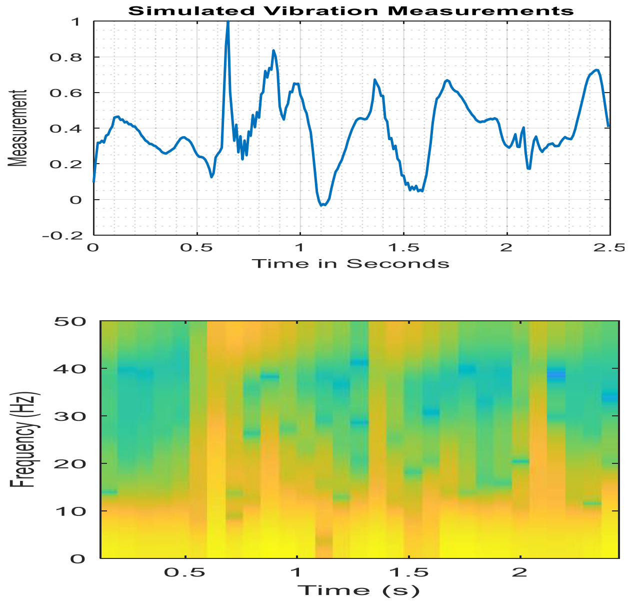


FIGURE 6. Temporal moments for walking and exercise signal patterns using the IM-WSHA dataset.

- In order to obtain transformed components, we convert the normalized power spectrum by the Shannon function: $(x) = y log 1/y$.

$$H_s(f) = Q_s\,(f)\,log\frac{1}{Q_s(f)} \tag{3}$$

- Finally, the obtained components H_s (f) are encapsulated together.

$$Entropy_s = \frac{\sum_f H_s(f_i)}{\log(N_s(f_1, f_2))} \tag{4}$$

where $(N_s f_1, f_2)$ is equal to the total number of components.

3) TEMPORAL MOMENTS

Temporal Moments captures signals pertaining to abrupt changes which involve abnormal patterns of human locomotion and falls. It delivers information about any speed changes occurring in a signal. These moments provide an efficient way to distinguish between signals whose frequencies vary over time. These moments extract the essential features of a signal without any computational overhead. Temporal moments can be estimated by:

$$m_i(a) = \int_{-\infty}^{\infty} (t-a)^i x^2(t)dt \tag{5}$$

where i^{th} is the temporal moment of $m_i(a)$, and $x(t)$ represents a time history of a time location.

4) MEL FREQUENCY CEPSTRAL COEFFICIENTS

Mel Frequency Cepstral Coefficients (MFCCs) are commonly used in speech synthesis systems [37]. They mainly focus the speech resolution on a lower scale. In this work, we adapted the feature extraction approach to inertial based

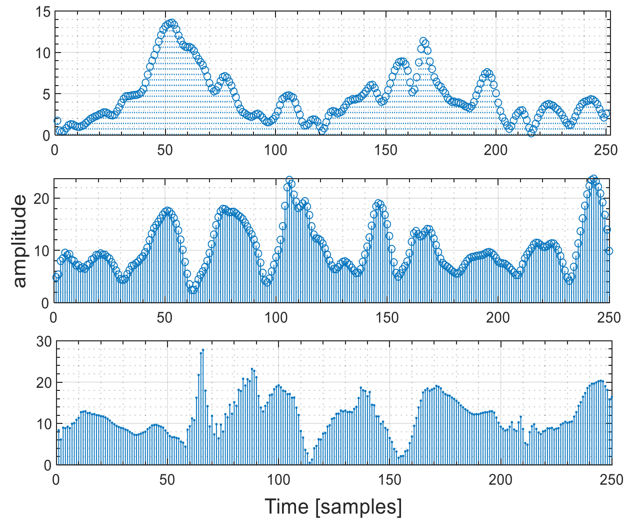


FIGURE 7. MFCC applied our inertial signal.

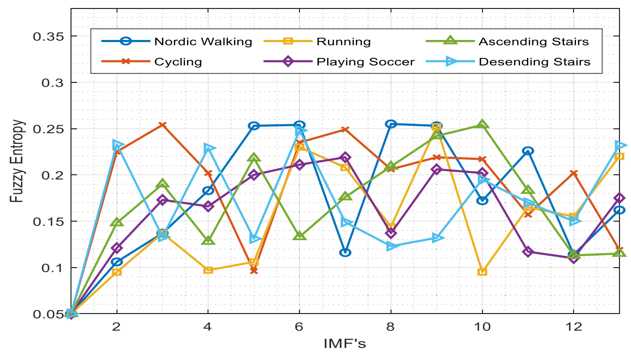


FIGURE 8. Fuzzy entropy for irregularity detection in six different locomotion activities which are more dynamic in nature.

sensors. Initially, we selected all the signals acquired from inertial sensors for further processing. However, the pre-emphasis step is adapted in speech signals due to the higher frequency range compared with other signals. Therefore, the frequency range is smaller in inertial signals so that this processing may be irrelevant. So, we can conclude that speech and inertial signals share similar energy distribution in smaller frequency ranges; consequently, MFCCs can be utilized for feature extraction in human locomotion analysis.

Initially, windowing and Fast Fourier Transform steps is performed to calculate the power spectrum of the inertial signal. Then, the power spectrum is mapped into the Mel scale to determine frequency band energies. The log of the power is computed on Mel scale frequencies and is carried to the Discrete Cosine Transform (DCT). Finally, the MFCC of inertial signals represents the amplitude spectrum.

$$MFCC(inertial) = \sum\nolimits_{j=0}^{n} s_n \cos[pj/n(j+0.5)k] \tag{6}$$

$$\text{inertial}(k) = \left\{ \begin{array}{l} \text{inertial}(j),\ k = k_j \\ 0,\ \text{other } k \in [0, N-1] \end{array} \right\} \tag{7}$$

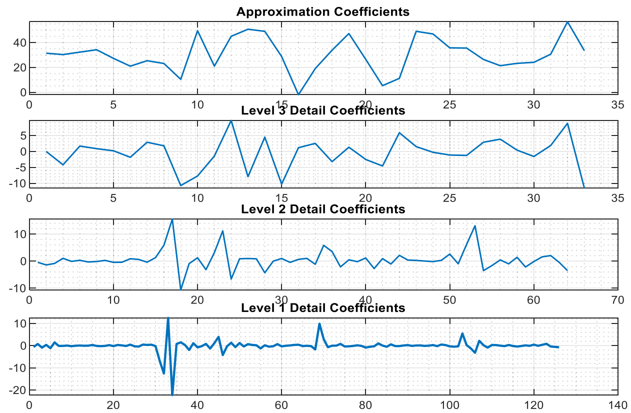


FIGURE 9. **Performing three level decomposition using computer activity to extract detailed and approximation coefficients.**

where s_n is the overall samples in each frame, j is the present sample of the signal, n denotes total samples of the present frame and k is the index of the observed samples.

5) FUZZY ENTROPY

Fuzzy Entropy is used as a method to detect any irregularities in signal data acquired from the inertial sensors [38]. Firstly, a processed inertial signal representing RPLBs is combined, and then Fuzzy Entropy is applied to measure any ambiguity in locomotion activities. The standard deviation is calculated and used to distinguish changes in static and dynamic activities in indoor-outdoor environments.

$$Fuzent(x, m, r, n, d) = -\ln\left(\frac{\psi^{m+1,d}(n, r)}{\psi^{m,d}(\mathrm{n}, r)}\right) \tag{8}$$

6) WAVELET DECOMPOSITION

Wavelet Decomposition is a systematic way to analyze the time-domain data of inertial signals. Wavelet decomposition of the signal also improves the recognition of variations that occur due to changes in any activity. For example, walking and running activities involve abrupt changes. Wavelet Decomposition enhances activity patterns and minimizes the noise arising from different activities (posture transitions). These transformations are an ideal method to extract meaningful information from signals.

Furthermore, the data obtained from inertial sensors can be split into detailed coefficients and approximation coefficients. These multiple coefficients are utilized for inertial signal analysis. In our work, approximation coefficients are fused to form a feature vector for further classification.

D. MULTI-FUSED FEATURE EXTRACTION METHODS

In the proposed approach, feature vectors are optimized via two popular optimization algorithms, namely, Stochastic Gradient Descent (SGD) and Adagrad. Vectors optimized by these optimization algorithms are fed to the kernel sliding perceptron (KSP) individually. Classification results of KSP are compared with Support Vector Machines and Artificial Neural Networks.

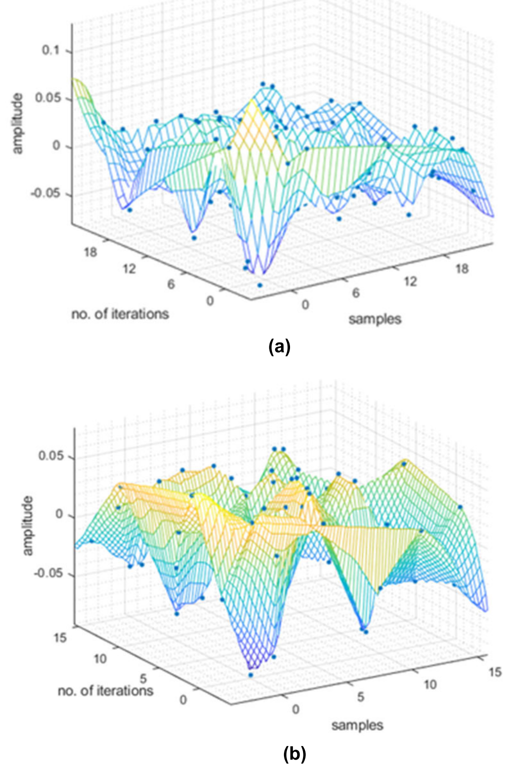


FIGURE 10. **Stochastic Gradient Descent (SGD) optimization algorithms with adaptive learning for (a) exercising and (b) walking activities using the IM-WSHA dataset.**

1) OPTIMIZATION USING STOCHASTIC GRADIENT DESCENT

Gradient Descent optimization algorithms develop a set of procedures that compute the adaptive learning rate to find an optimal set of features with a minimum cost function. However, the gradient descent algorithm may perform slowly while processing all the training data in each epoch and when the training data size is large. In order to overcome this problem, Stochastic Gradient Descent algorithm (SGD) with minibatch is introduced as an optimizer which does not use all of the training data. It also does not use the single data point [39]. However, minibatch SGD fused randomly selects a set of data to reduce cost and attain lower variance than the traditional SGD. Therefore, minibatch requires careful observation while using adaptive learning rates with initial parameters in order to produce minimum loss function. So, the learning rate of 0.01 is adapted with regularization parameter values which are tuned by Leave One Subject Out (LOSO) cross-validation to minimize the loss function. SGD of all the training data for $x^{(k)}$ and $y^{(k)}$ labels is denoted as:

$$\theta = \theta - \eta \cdot \nabla_\theta J\left(\theta; x^{(k)}; y^{(k)}\right) \tag{9}$$

where n_{bs} is minibatch size, therefore it attains the lower variance of initial parameters and produces minimum loss function.

$$\theta = \theta - \eta \cdot \nabla_\theta J\left(\theta; x^{(k:k+n_{bs})}; y^{(k:k+n_{bs})}\right) \tag{10}$$

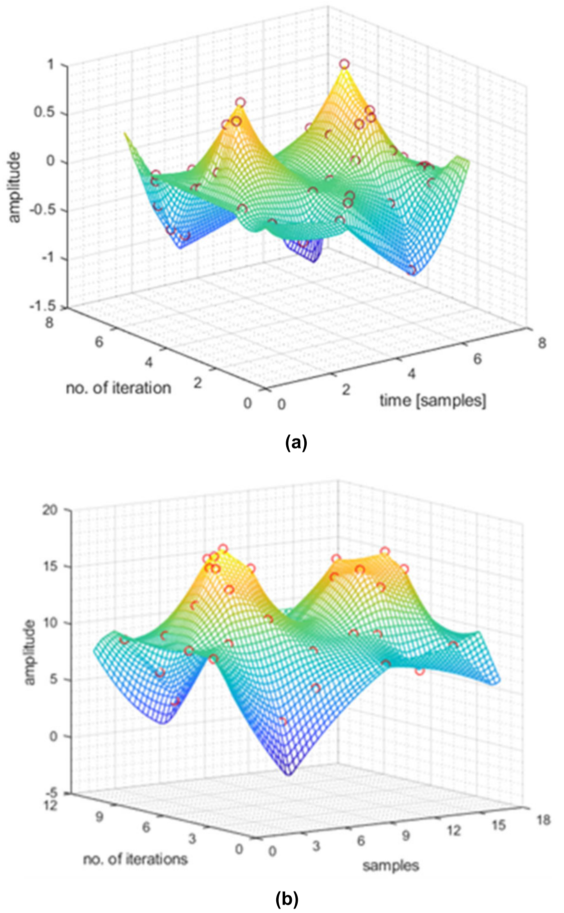


FIGURE 11. Adagrad optimization algorithm with adaptive learning for (a) ironing and (b) cooking activities using the IM-WSHA dataset.

2) OPTIMIZATION USING ADAGRAD

The proposed system is also evaluated with an Adagrad optimization-based algorithm along with the kernel sliding perceptron. Adagrad optimization [40] scales the learning rate for each component and reduces the learning rate faster for frequent parameters and updates more slowly for sporadic data. Therefore, it is well suited to sparse parameters.

At first, Adagrad parameters are updated for every dimension, and then vectorization is performed. In eq.11, $\theta_{t,e}$ is used to set the gradient of the objective function for the parameter c, at time t:

$$g_{t,e} = \nabla_{\theta_t} J\left(\theta_{t,e}\right) \tag{11}$$

At time step t, every parameter θ_e for update becomes:

$$\theta_{t+1,e} = \theta_{t,e} - \eta \cdot g_{t,e} \tag{12}$$

Finally, Adagrad adapts the learning rate η at each time t for dimension θ_e:

$$\theta_{t+1,e} = \theta_{t,e} - \frac{\eta}{\sqrt{G_{t,ii} + \epsilon}} \cdot g_{t,e} \tag{13}$$

Algorithm 2 Real-Time Personal Locomotion Behavior Recognition by Kernel Sliding Perceptron

Input: Multi-fused features from time, wavelet, and time-frequency domain
Output: R: Recognized Human Locomotion based Activities

m$_i$ = maximum no. of iterations,
$\beta = \{\beta_1, \beta_2, \beta_3, \ldots .\beta_n\}$
Initialization of $\beta c = 0$ for each c
while vector in((t) and k <= m$_i$)
t = 0;
for(c = 1 : m$_i$)
if $y_c^* \left(\sum_{r=1}^{mi} \beta_r k\left(z_c, z_r\right)\right) \le 0$
t = t+1;
$\beta c = \beta c - 1 + yjzj$
end
end
k = k+1;
end
return R

3) KERNEL SLIDING PERCEPTRON

After optimal feature selection, we evaluated the proposed model against three benchmark datasets that involve locomotion activities for multiple classes. The optimized features of SGD and Adagrad are separately classified by a novel classifier Kernel Sliding Perceptron (KSP) with Multilayer Perceptron (MLP) to improve classification accuracy. Quantized feature vectors are fed to the KSP as input. Kernel transforms the fused vectors into an intermedial space and slides the kernel-based features to link the MLP by calculating the feature pairs as:

$$\text{class}(z) = \arg_i max\,\text{sign}\left(\sum_{c=1}^{T} \beta_c k\left(z_c, z\right)\right) \tag{14}$$

where T depicts the training examples and β_c is the total weight assigned to the training example. Moreover, the predicted outcome is contrasted with a truth table where, if both remain true, accurate recognition can be achieved. However, in cases where comparisons are not true, weight values are updated and are correlated with incorrect instances as:

$$\beta_c = \beta_{c-1} + y_c z_c \tag{15}$$

where β_{c-1} is updated against old weights and $y_c z_c$ is the incorrect training instance. Algorithm 3 defines the flow of kernel sliding perceptron for real-time personal locomotion behavior recognition.

Figure 12 illustrates the overall system architecture of kernel sliding perceptron, which comprises only one input and output and one hidden layer perceptron. Initially, the Input layer took the selected optimal features from SGD and Adagrad separately and fused the features to the output layer which consists of multilayer perceptron depending on the number of classes in our training dataset.

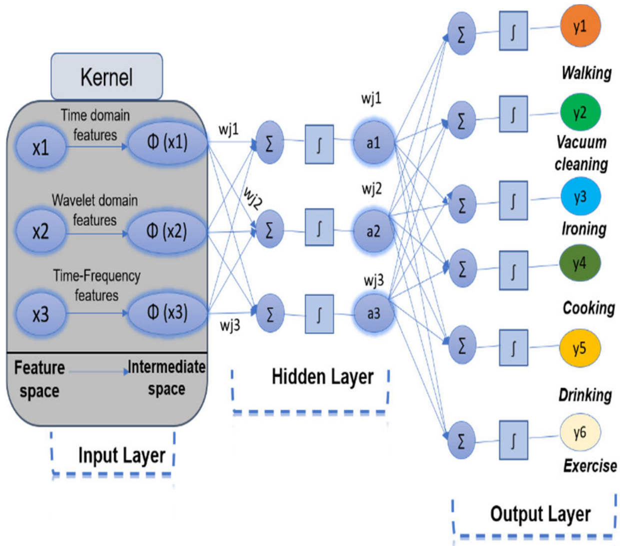


FIGURE 12. Architecture of Kernel Sliding Perceptron over IM-WSHA dataset.

IV. EXPERIMENTAL SETTING AND ANALYSIS

All experiments are executed on a laptop equipped with Intel Core i5-6200U 2.40GHz processing power, 8GB RAM, 2 GB dedicated graphics card Nvidia 920M having ×64 based Windows 10 pro and using MATLAB and Google Colab (Python) tools. Moreover, a platform is set up to evaluate the performance of our proposed model performed on three datasets, namely, our self-annotated IM-WSHA dataset along with PAMAP-2 and HuGaDB benchmark datasets. To observe the validation performance of our RPLB system for indoor-outdoor environments, we used the leave-one-subject-out cross validation (LOSO) method.

A. THE "INTELLIGENT MEDIA - WEARABLE SMART HOME ACTIVITIES" (IM-WSHA) DATASET

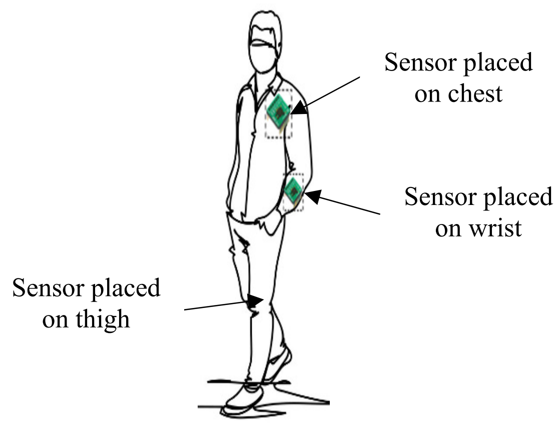
The IM-WSHA dataset [41] is our self-annotated dataset which embodies data from three inertial sensors, namely, tri-axial accelerometers, gyroscopes, and magnetometers. These inertial sensors are placed at three different body locations (chest, thigh, and wrist) to capture essential aspects of human locomotion behaviors in real-time. 10 subjects (five males, five females) performed 11 different activities in the smart home environment: *brushing hair, cooking, drinking, exercise, ironing, phone conversation, reading book, using computer, vacuum cleaning, watching tv and walking.*

1) HARDWARE PLATFORM

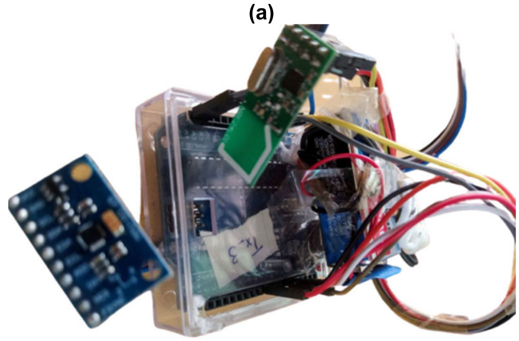
The hardware platform involved three inertial MPU-9250 sensors. All sensors were interfaced with Arduino Uno for communication and NRF24L01 wireless transceiver modules were linked with MPU-9250 sensors. All the modules comprising MPU-9250, NRF24L01, and Arduino Uno along with a 9-volt battery were fixed in a uniquely designed Arduino protective case. The Arduino cases with integrated modules were mounted on a belt and tied securely at the subject's wrist, thigh, and chest (see Figure 11) ensuring sustained physical support. Moreover, the open-source IDE Arduino tool was utilized to simulate experiments in real-time environments.

TABLE 1. Locomotion activities with labels in IM-WSHA dataset.

Activity Name	Duration or Repetition	Description
Using Computer	1 min	using computer while sitting on chair
Phone Conversation	1 min	lying down
Vacuum Cleaning	1 min	cleaning room in standing position
Reading Book	1 min	lying down
Watching Tv	1 min	sitting on chair
Ironing	1 min	sitting down
Walking	1 min	walking on floor
Exercise	1 min	bending arms and legs
Cooking	1 min	standing
Drinking	20 x	standing
Brushing hair	20 x	standing



(a)



(b)

FIGURE 13. (a) Placement of the sensors (MPU-9250) on the wrist, chest, and thigh for data acquisition from the self-annotated IM-WSHA dataset and (b) sensor setup comprising MPU-9250, Arduino Uno, and NRF24L01 wireless module along with a 9-volt battery with protective case.

B. PHYSICAL ACTIVITY MONITORING FOR AGING PEOPLE (PAMAP2) DATASET

The benchmark PAMAP2 dataset [42] is taken from three inertial sensors made up of triaxial accelerometers, gyroscopes, and magnetometers located on the subject's ankle, chest, and wrist regions to perform 18 house-hold activities.

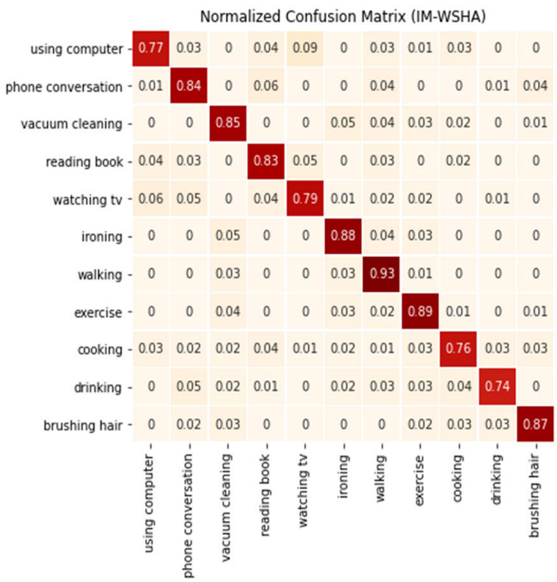


FIGURE 14. Confusion matrix of 11 different human locomotion activities on the IM-WSHA dataset using Kernel Sliding Perceptron.

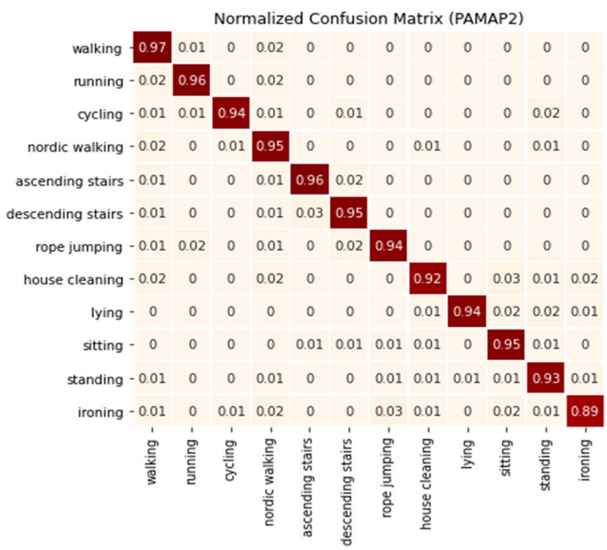


FIGURE 15. Confusion matrix of 12 different physical activities on the PAMAP2 dataset using Kernel Sliding Perceptron.

We evaluated 12 activities of this dataset including, *walking, running, cycling, Nordic walking, ascending and descending stairs, rope jumping, house cleaning, lying down, sitting, standing,* and *ironing*. This dataset involves extended and repetitive household physical activities typical for RPLB systems targeted to analyze different motion patterns.

C. HUMAN GAIT DATABASE (HuGaDB)

The third dataset [43] embodies motion data from six inertial sensors which were placed at the left and right thighs, feet, and shins. A group of 18 healthy subjects performed 12 different activities: *sitting in a car, up and down by elevator, standing and standing up (from sitting position), sitting, and sitting down (from standing position), bicycling, going up and down the stairs, running and walking.* This dataset involves both static and dynamic activities which make it challenging in nature.

TABLE 2. Comparison of recognition accuracy of the proposed method with other state-of-the-art methods over IM-WSHA, PAMAP2 and HuGaDB datasets.

Methods	IM-WSHA (%)	PAMAP2 (%)	HuGaDB (%)
Support Vector Machine	72.84	87.34	85.68
Deep Convolutional and LSTM RNN [44]		74.80	
Confidence-based Multiclass AdaBoost [45]		77.78	
Artificial Neural Network	80.13	88.93	91.23
Kinematics features with kernel sliding perceptron [46]	81.47	90.49	91.76
Estimation algorithm [47]	80.49	91.46	90.37
Complexity measures [48]	78.47	86.93	85.91
Proposed RPLB + Adagrad	81.73	92.84	89.90
Proposed RPLB + Stochastic Gradient Descent	83.18	94.16	92.50

D. PARAMETER EVALUATION VIA RECOGNITION ACCURACIES

In this experiment, we evaluate the performance of the novel kernel sliding perceptron by providing optimized feature descriptors of time, wavelet, and time-frequency using the IM-WSHA, PAMAP2 and HuGaDB datasets.

In order to evaluate the performance of the proposed system over three benchmark datasets, the experiment was repeated three times. Figure 12 illustrates the confusion matrix over the IM-WSHA dataset for 11 human locomotion activities, where an accuracy rate of 83.18% was obtained. Figure 13 depicts a mean recognition rate of 94.16% over 12 different physical activities in the PAMAP2 dataset. Figure 14 represents the confusion matrix of the HuGaDB dataset over 12 activities, where a mean accuracy rate of 92.50% was achieved.

Table 2 represents the comparison results between the proposed method and other state-of-the-arts methods. In Tables 3-5 we evaluated the performance of the proposed system by comparison it with two other state-of-the-art methods, namely, Multilayer Perceptron (MLP) and Artificial Neural Network (ANN) classifiers using precision, recall, and F1 scores of all classes used in these datasets: IM-WSHA, PAMAP2, and HuGaDB.

TABLE 3. Measurements of evaluation metrics of proposed method over IM-WSHA dataset.

IM-WSHA	Kernel Sliding Perceptron			Artificial Neural Network			Support Vector Machine		
Activities	Precision	Recall	F-measure	Precision	Recall	F-measure	Precision	Recall	F-measure
L1	0.846	0.770	0.806	0.813	0.765	0.788	0.791	0.764	0.777
L2	0.807	0.840	0.823	0.767	0.785	0.775	0.723	0.719	0.720
L3	0.809	0.850	0.829	0.780	0.792	0.785	0.729	0.698	0.713
L4	0.813	0.830	0.821	0.790	0.793	0.791	0.741	0.687	0.711
L5	0.822	0.790	0.806	0.754	0.704	0.728	0.697	0.713	0.709
L6	0.846	0.880	0.862	0.814	0.832	0.822	0.758	0.706	0.731
L7	0.781	0.930	0.849	0.689	0.764	0.724	0.703	0.684	0.693
L8	0.831	0.890	0.859	0.797	0.845	0.820	0.732	0.691	0.710
L9	0.835	0.760	0.795	0.784	0.698	0.738	0.765	0.732	0.748
L10	0.902	0.740	0.813	0.819	0.684	0.745	0.722	0.710	0.715
L11	0.878	0.870	0.874	0.776	0.754	0.764	0.763	0.720	0.740

TABLE 4. Measurements of evaluation metrics of the proposed method over PAMAP2 dataset.

PAMAP2	Kernel Sliding Perceptron			Artificial Neural Network			Support Vector Machine		
Activities	Precision	Recall	F-measure	Precision	Recall	F-measure	Precision	Recall	F-measure
P1	0.889	0.970	0.928	0.826	0.785	0.804	0.803	0.754	0.777
P2	0.960	0.960	0.960	0.887	0.792	0.836	0.848	0.758	0.800
P3	0.979	0.940	0.959	0.942	0.810	0.871	0.896	0.784	0.836
P4	0.887	0.950	0.917	0.767	0.789	0.777	0.725	0.701	0.712
P5	0.960	0.960	0.960	0.896	0.810	0.850	0.828	0.748	0.785
P6	0.940	0.950	0.945	0.865	0.799	0.830	0.836	0.856	0.845
P7	0.949	0.940	0.944	0.881	0.776	0.825	0.789	0.747	0.767
P8	0.948	0.920	0.934	0.893	0.793	0.840	0.732	0.709	0.720
P9	0.989	0.940	0.964	0.901	0.803	0.849	0.841	0.748	0.791
P10	0.931	0.950	0.940	0.864	0.795	0.828	0.885	0.780	0.829
P11	0.920	0.930	0.925	0.829	0.789	0.808	0.799	0.751	0.774
P12	0.956	0.890	0.922	0.854	0.792	0.821	0.838	0.756	0.794

We compared one of the dataset including PAMAP2 with Kernel sliding perceptron (KSP) and Artificial neural network (ANN). In addition, results show KSP has attains good classification scores over ANN. As shown by Figure 17 and 18, we can easily discriminate all 11 classes in PAMAP2 dataset.

V. DISCUSSIONS

Our adaptation of the RPLB framework attained high F1 scores and recognition rates in the sensor data. Initially, we utilized three IMU sensors on different body locations to achieve better information regarding the orientation and rotation of various aspects of the body. Then, all datasets were denoised with a 3rd order median filter to eliminate noise without changing the original signal. Filtered data is further processed with a sliding window approach that effectively recognizes static and dynamic activities. Furthermore, using multiple descriptors in different domains (time, wavelet, time-frequency), the proposed system produces better performance. Statistical features have less computational overhead, but using all descriptors can attain more information about static and dynamic activities. Next, acquired features are optimized through SGD and Adagrad to select meaningful features. Finally, different classifiers are applied to evaluate the performance of the proposed system. In addition, locomotion behaviours are classified over the kernel sliding perceptron which attained better recognition rate performance over other state-of-the-art methods.

The following are limitations of the proposed sensor fusion method.

TABLE 5. Measurements of evaluation metrics of the proposed method over HuGaDB dataset.

HuGaDB	Kernel Sliding Perceptron			Artificial Neural Network			Support Vector Machine		
Activities	Precision	Recall	F-measure	Precision	Recall	F-measure	Precision	Recall	F-measure
H1	0.930	0.930	0.930	0.818	0.745	0.779	0.804	0.732	0.766
H2	0.900	0.910	0.905	0.836	0.754	0.792	0.812	0.741	0.774
H3	0.908	0.890	0.898	0.843	0.761	0.799	0.823	0.759	0.789
H4	0.865	0.900	0.882	0.788	0.734	0.760	0.765	0.723	0.743
H5	0.885	0.930	0.907	0.834	0.761	0.795	0.856	0.765	0.807
H6	0.900	0.910	0.905	0.841	0.776	0.807	0.832	0.772	0.800
H7	0.929	0.920	0.924	0.867	0.781	0.821	0.851	0.781	0.814
H8	0.949	0.940	0.944	0.882	0.799	0.838	0.891	0.812	0.849
H9	0.928	0.910	0.919	0.832	0.756	0.792	0.823	0.734	0.775
H10	0.958	0.930	0.944	0.890	0.791	0.837	0.889	0.786	0.834
H11	0.979	0.960	0.969	0.911	0.884	0.897	0.795	0.751	0.772
H12	0.970	0.970	0.940	0.904	0.881	0.779	0.837	0.781	0.766

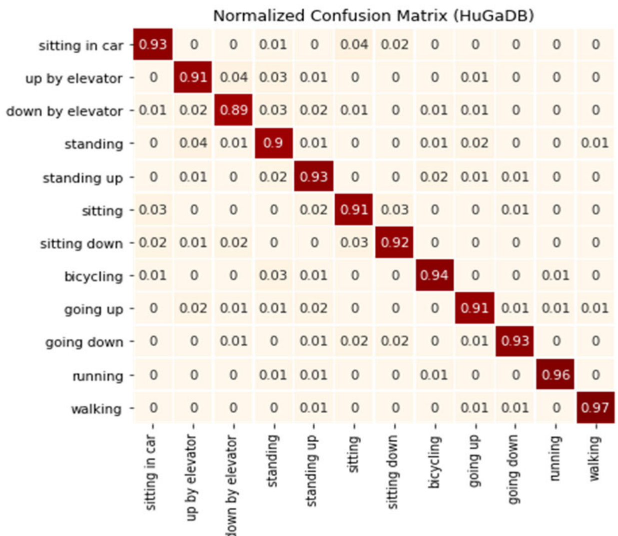


FIGURE 16. Confusion matrix of 12 life-log activities on the HuGaDB dataset using Kernel Sliding Perceptron.

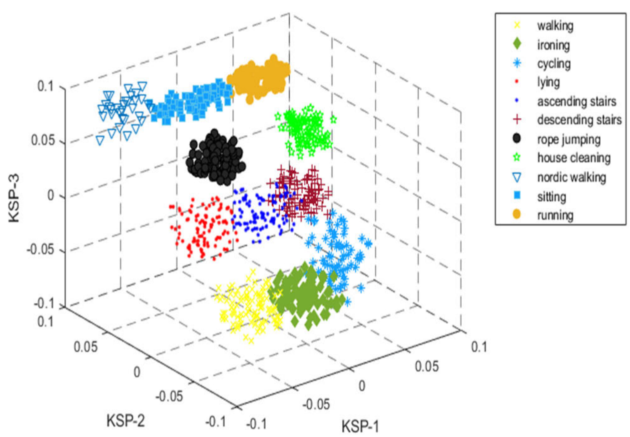


FIGURE 17. Kernel Sliding Perceptron classification on the PAMAP2 dataset.

- The combination of inertial sensors is promising, however, this could produce problems related to the robustness and precision of individual sensors.
- During any activity, a volunteer may significantly adjust his/her speed and sometimes even stop in the middle of a random activity. Hence, it is not feasible to include the optimal low count number.
- The combined-sensors setup can work for up to two days with 9-volt batteries. Thus, it is recommended to monitor and recharge or change the battery so that no interruption can occur during experimentation.
- One of the main limitations of RPLB algorithms is transfer learning, where knowledge attained by an individual IMU sensor located on a specific body position can be reused by multiple sensors in different locations. This potential to transfer learning can be helpful in many scenarios has not been analyzed in a detailed manner.
- Our proposed approach does not cater to a no activity state (inactivity) even though it is automated to detect these patterns due to its similarity to some relatively inactive states like sitting, lying down and standing.

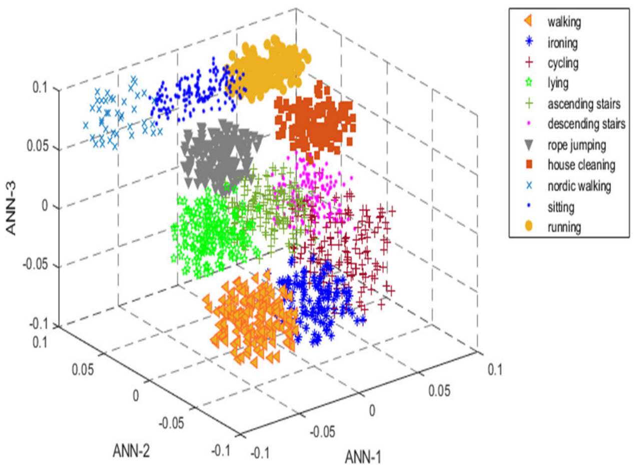


FIGURE 18. Artificial neural network classification on the PAMAP2 dataset.

The proposed approach can only monitor gait patterns which comprise smoothness in the way motion pattern shambles. Any ambiguous information to the proposed method interrupts the pattern recognition ability unless the subject performs a consistent transition.

It can be concluded from the experimental results that the combination of the sensors provides better detail regarding human body movements. The multi-fused features time, wavelet, and time-frequency domain features computed from IMU sensors improve the recognition accuracy of the proposed system compared to other state-of-the-art SVM, ANN, deep convolutional methods. Regarding the performance of the classifiers, the Kernel sliding perceptron delivers better results for the proposed RPLB system.

VI. CONCLUSION AND FUTURE WORK

In this paper, an RPLB approach based on multi-fused features, including time, wavelet, and time-frequency features is proposed. Features are optimized by SGD and classified via Kernel Sliding Perceptron to enhance the recognition rate of human locomotion activities via three inertial based body-worn sensors. These multi-fused features analyze the temporal moments, optimal patterns, invariable and repetitive patterns in motion to improve the performance of the RPLB based system. In addition, these features are optimized by stochastic gradient descent (SGD) and passed through the kernel sliding perceptron (KSP). This paper also compares the performance of the KSP classifier optimized by Adagrad with Artificial Neural Network (ANN) and Support Vector Machines (SVM). During experimentation, we used three benchmark datasets including PAMAP2, HuGaDB dataset and our self-annotated dataset called IM-WSHA. Experimental result proved that the proposed method can significantly improve the recognition rate of human locomotion activities.

In future work, we will adapt more complex activities from different scenarios such as smart homes, healthcare centers, and office environments via multiple inertial based sensors.

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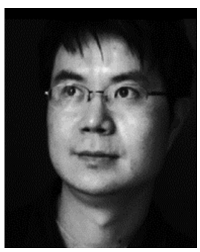

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