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MS-DLD: Multi-Sensors Based Daily Locomotion Detection via Kinematic-Static Energy and Body-Specific HMMs

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ABSTRACT More adaptable and user-independent techniques are required for multi-sensors based daily locomotion detection (MS-DLD). This research study proposes a couple of locomotion detection methods using body-worn multi-sensors to successfully categorize several locomotion transitions. This research presents both standard and state-of-the-art methods for MS-DLD. Conventionally, to improve MS-DLD process, the proposed methodology consists of a wavelet transformed Quaternion-based filter for the inertial signals, patterns recognition in the form of kinematic-static energies, and state-of-the-art multi-features extraction. These features include entropy, spectral, and cepstral coefficients domains. Then, fuzzy logic-based optimization has been introduced in order to achieve the selective features by converting them into codewords. These nominated features with enhanced patterns are further detected by HMMs to improve the accuracy for classifying daily life locomotion actions. This paper also introduces another state-of-the-art way to model daily locomotion detection and derives body-specific modified HMMs. The model divides the sensor data into three active body-specific parts including head sensors, mid-body sensors, and lower body sensors. Body-specific modified HMMs have been provided with raw data for the three active body-specific sensors and gave better results with less computational complexities when compared to the conventional methods. The proposed systems have been experimentally assessed and trialed over three diverse publicly available datasets: the UP-Fall dataset consisting of falling and other daily life activities, the IM-WSHA dataset comprising everyday locomotion actions, and the ENABL3S gait and locomotion dataset consisting of multiple gait movements. Experimental outcomes indicate that the proposed conventional technique achieved improved results and outperformed existing systems based on detection accuracies of 90.0% and 87.5% over UP-Fall, 86.0% and 88.3% over IM-WSHA, and 86.7% and 90.0% over ENABL3S datasets for kinematic and static energy patterns, respectively. Further, the results show that the state-of-the-art body-specific modified HMMs method achieved 94.3% and 95.0% over UP-Fall, 92.0% and 93.3% over IM-WSHA, and 90.0% and 95.0% over ENABL3S datasets for kinematic and static patterned signals, respectively. The results of state-of-the-art efficient system show a significant increase in detection accuracy when compared to standard systems.

INDEX TERMS Body-worn sensors, filter, healthcare monitoring, hidden Markov models, locomotion detection, machine learning, noise reduction, patterns recognition.

I. INTRODUCTION

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Humans perform distinct locomotion actions in their daily lives. Recently, the demand to advance human health and

well-being using body-worn fused multi-sensors technologies has increased. The purpose of monitoring locomotion actions via body-worn fused multi-sensors is to trace daily routines in order to protect humans as they engage in their lives [1]. Fortunately, in this area of research more features and methodologies are evolving along with a fusion of multi-sensors. Improvements in body-worn multi-sensors, such as electromyography (EMG), electroencephalography (EEG), accelerometer, gyroscope, magnetometer, and electrocardiography (ECG), have expanded research capacities and fortified the progress of new daily locomotion detection (DLD) applications [2], including online health services, recovery centers, safety observations, emergency facilities, healthcare assistance, and bio-feedback systems [3]–[7]. All these practices need regular check-ups and follow-ups. Multiple applications of inertial sensors can be seen in the literature. Body-worn inertial measurement units (IMUs) can monitor, record, and transfer vital information for healthcare, fitness decisions, and locomotion transitions that help in tracking and safeguarding human health [8]. However, these sensors can only gather partial information on locomotion actions.

There are multiple systems available in the literature that attempted to resolve the problem of human locomotion detection using single type of sensors, however, others have combined different kinds of sensors to achieve the goal. Single form of sensors such as IMUs-based systems have been able to monitor the human locomotion for simple movements and couldn't achieve acceptable results for the complex motion patterns. Similarly, a few IMU-based methods achieved good accuracies for static locomotion while performance dropped down for the dynamic locomotion.

To avoid the limitations related to privacy and power consumption [9], biosensors, such as EEG, EMG, and ECG, can provide further support in sensing difficult-to-track activities and understanding those activities for DLD. This fusion with inertial sensors can help in tracking 3-dimensional body locomotion along with heart-, brain-, and muscular-related statistics. Acceleration provides variations in speed, a gyroscope gives the rate of change in angular motion, and a magnetometer provides relative changes in magnetic energy. An ECG provides the electrical signals from the heart, an EMG delivers the information about muscle health, and an EEG detects the electrical activity in the brain. Whereas, many locomotion actions, such as walking and jogging, have different characteristics as part of their signals can be similar. These similarities in signal behaviors make it difficult to detect daily locomotion.

By looking at the fused sensors-based systems in literature, there were a few shortcomings that our proposed methods have focused on. A couple of studies are based on outdoor locomotion lacking to show the effectiveness over multiple types of environmental settings. Some research works are based on limited age groups of humans ignoring the fact that different age groups can have different effect on the system outcome. A few researchers focused on limited sensor

positions, which can limit the system's efficacy in real-time environment.

A sophisticated technique known as explicit complementary filter (ECF) has been proposed in [10]. The filter has been proposed for the monitoring of improper sitting postures. IMUs have been placed on back of the subject and are restricted to calculate the angles of movement in the upper part of body only. Our proposed method is effective for the complete body posture movements. The experimental results in ECF-based study showed that as the true angle of movement increases in both positive and negative directions, the mean square error increases. However, our proposed study suggests no such errors due to the angle variations in postures for DLD.

Traditionally, the sensors placed on different body-parts have been considered for processing in a system in order to detect locomotion behavior. Our approach focuses on body-specific active sensors that are involved in a particular locomotion. Hence, avoiding the extra information processing and errors that can cause overall performance degradation. In [11], the system for joint-specific hidden Markov models (HMMs) has been proposed for human activity recognition. Their focus is on the data from stereo posture image sequences and joint-specific HMMs. However, the method will not be able to detect motion patterns if there is no movement in the body joints. The proposed MS-DLD system has utilized the body-worn sensors and able to retrieve locomotion from the joint-free data by focusing on active sensors placement.

For conventional systems, the complex motion patterns are difficult to be detected due to extreme variations and similarities in the signal characteristics. Therefore, standard MS-DLD system has introduced a pre-classification method that supports in the detection of kinematic and static signal patterns before the features extraction phase. These kinematic-static patterned signals help in detecting the human locomotion better than conventional systems.

The proposed method, multi-sensors-based daily locomotion detection (MS-DLD), provides two unique ways of classifying DLD (falling, walking, jogging, jumping, etc.): standard kinematic-static energy patterns detection and body-specific modified hidden Markov models (HMMs):

1. Conventionally, kinematic-static energy patterns are being detected by measuring changes in body location, gyration, orientation, and brain-, muscle-, and heart-specific data. The main idea is to improve the DLD accuracy while keeping the system complexity components in mind for locomotion. The proposed MS-DLD system consists of seven main steps: denoising of data from the sensors, multi-sensors data fusion, making windows of data for processing, identifying static and kinematic energy patterns, extracting the features for both the patterns, optimizing the extracted features into codewords, and applying accumulated HMMs for classification, which will support the ability to achieve good accuracy [12].

2. Body-specific modified HMMs are trained according to the sensors' placement in different locomotion actions along with zero processing of data. The focus is on individual body parts instead of the entire body at once, which is different from any conventional approach. The study discussed in this paper proposed a new technique of classifying activities and developed body-specific modified HMMs.

To test the performance of these two methods, this study recommended cross-validation with 10-folds [13] on three benchmark datasets: UP-Fall [14], IM-WSHA [15], and ENABL3S [16]. The IMUs data acquired from UP-Fall dataset has been pre-processed using a state-of-the-art wavelet transformed Quaternion (WTQ)-based modified filter. The EEG data has been cleansed using a Butterworth filter. The IMUs and biosensor data have been fused and windowed for further processing. Then, acceleration, angles, and phase information have been retrieved from the fused and windowed data to identify the kinematic and static energy patterns among different locomotion actions. A variety of feature extraction techniques, including entropy, cepstral, and spectral domains, have been used for both recognized patterns. Due to the dimensionality issue, the features have been converted into codewords using the fuzzy logic-based optimization technique. As a final point, a multi-layered HMM has been applied for DLD while achieving significant accuracy. To estimate the performance, the proposed methodology has been applied to three diverse publicly available datasets, namely, UP-Fall, ENABL3S, and IM-WSHA, which have different shapes of human locomotion transitions.

The same datasets have been utilized for the body-specific modified HMMs. The key contributions and high points obtained of this study are:

- A MS-DLD system has been proposed using two unique techniques: kinematic-static energy patterns recognition and body-specific modified HMMs.
- A state-of-the-art modified filter for IMUs, called WTQ-based filter, has been introduced to provide primarily error-free motion data for all the locomotion actions.
- A kinematic-static energy pattern identification method has been presented to pre-classify locomotion actions into two categories making it more viable for the classifier.
- A body-specific modified HMMs technique has been proposed to classify from the raw sensors data based on sensors placed on specific body parts and unlike the conventional approaches avoiding the need to go through different phases from pre-processing to classification.
- Moreover, a thorough comparative study has been conducted using the three publicly available datasets for diversified human DLD. The experimental outcomes demonstrate that a higher detection accuracy has been achieved using the MS-DLD systems in comparison to some other existing methodologies.

- The body-specific modified HMMs based system outperformed all the conventional approaches including the proposed standard method.

The remainder of this paper has been organized as follows. Section II presents a literature review of the existing methods. Section III discusses the proposed systems containing MS-DLD. Section IV presents the experimental structure and discusses the effects of the projected system using three datasets along with an evaluation of existing systems. Finally, Section V provides an explanation of the perceptions obtained from the experimentations. Section VI presents the conclusion and recommends the future research direction.

II. RELATED WORK

Multiple methods have been proposed by different scholars for DLD utilizing a diverse range of sensors such as IMUs, biosensors, and fused sensors. This section presents a literature review on inertial-based DLD systems and fused sensors-based DLD systems.

A. DLD VIA IMU SENSORS

In IMU-based DLD systems, many experts have engaged accelerometer, gyroscope, and magnetometer sensors from IMUs, which are mostly used for healthcare monitoring and detection of locomotion and disease in individuals. Jalal *et al.* [15] produced a dataset for individual physical healthcare actions recognition (phone conversation, cleaning, using computers, etc.) via three wearable IMU sensors. In addition, they have utilized both statistical and non-statistical combination of features for the analysis of eleven dissimilar activities for IM-WSHA, six activities for WISDM, six activities for IM-SB, and three activities for SMotion. However, healthcare monitoring using inertial-based systems is suitable for simple locomotion actions. On the other hand, the system didn't give appropriate results for the complex locomotion. In [17], Quaid *et al.* suggested a novel idea for social behavior pattern recognition. This method was based on the statistical relation between behavior and signals using acoustic features extraction. Then, these features were reweighted to segregate the behaviors. The reweighted features were further treated by biological procedures of crossover and mutation to acclimate fluctuating signal patterns. The proposed method showed good results for static locomotion detection such as sitting, standing, brushing, etc. But when it comes to dynamic locomotion detection such as cycling, badminton, skipping, etc., the system was not very accurate. Gochoo *et al.* [8] have dealt with the dominant issues in the monitoring of physical activities recognition such as inaccurate features extraction persuaded by improper detection of locomotion actions. To solve this problem, a hierarchical feature-based approach along with kernel sliding perceptron was proposed. However, this technique did not comparatively stand for the fundamental characteristics of human locomotion, but it was useful in detecting complex locomotion including stairs ascend, descend, cycling, etc.

Jalal *et al.* [18] focused on the conventional way of system frameworks. They proposed inertial data filtering, time and frequency domain features extraction, optimization, and finally K-Ary tree hashing classifier-based approach. The system was evaluated on three datasets DALIAC, IM-LifeLog, and PAMPA2 containing multiple daily life activities. In [19], Tahir *et al.* proposed an SMO-based random forest activity analysis model for recognizing robust human activities. They divided the model into four components (filtration, features representation, pre-classification, and classification). They have used USC_HAD and IMSB datasets for experimentation. But the proposed method couldn't provide good results in terms of detection accuracy. Batool *et al.* [20] introduced a behavioral activity detection framework to recognize the activities within the home environment using multiple features and a reweighted genetic algorithm. The technique consists of data segmentation, denoising data, features retrieval, features optimization, data classification, and tele-monitoring. However, the offered approach lacks experiments on complex datasets, which encompass fall and other physical exertion data. In [21], Tahir *et al.* projected a human activity recognition model to recognize human motion using multiple filters, statistical, wavelet, and binary features, Adam optimization, and maximum entropy Markov model-based classification.

B. DLD VIA FUSED SENSORS

Current developments in body-worn sensors have been effectively instigated by scientists to observe daily locomotion without any interruptions. In an attempt to monitor DLD, scholars have suggested a fusion of multiple types of sensing devices to discover a more competent way of detecting locomotion actions and to enhance healthcare systems. Javeed *et al.* [9] proposed a wearable sensors-based system to extract multi-features. They also introduced a fused sensors-based technique to categorize signals into three classes to detect individual exertion. That study also utilized a data segmenting dataset, which was based on IMU, EMG, and MMG data. However, that study did not deal with the absent data that breaks the stability of locomotion actions, resulting in diminishing the system's performance. Moreover, their proposed methodology was evaluated against one dataset, which is not enough to show promising results. In [22], Zhang *et al.* developed a multi-sensors-based wearable system via fusion of body-worn IMUs and electrophysiology sensors such as EEG, ECG, and EMG. The process includes denoising data, segmenting, and frequency calculation. However, their experimental approach with detection in the clinical environment lacked the home setting scenario for recognition of disease symptoms recognition.

Krausz *et al.* [23] developed a sensor fusion-based forward predictor that incorporates environmental data, recorded from multiple wearable sensors and vision-based sensors. They also introduced a feature-driven approach to perform DLD. The features included mean, standard deviation, waveform length, zero crossings, slope sign changes, etc. However,

the drawback of this effort is that only young subjects, ranging in age from 23 to 29 years, were studied. In [13], Javeed *et al.* presented hybrid features for a sustainable physical healthcare patterns recognition model via different body-worn sensors. Moreover, the method has used IMU, EMG, and ECG signals to be filtered and windowed followed by features extraction, fusion, and selection techniques. That study also used Gaussian mixture model along with Gaussian mixture regression based optimization and a deep belief network has been utilized for classification. However, their proposed approach was only utilized on two similar kind of datasets to detect human activities. In [24], Jia *et al.* offered a novel scheme for detecting daily human living activities by fusing IMU and ECG data. They extracted both time and frequency features from raw sensor data. To handle dimensionality issues, they proposed a linear discriminant analysis (LDA) scheme. Then, these reduced features were classified using relevance vector machines and all the sensor results were finally fused together at the decision level to enhance the overall performance. However, this system trial was performed on four subjects only, which is not sufficient. Zdravetski *et al.* [25] introduced a model to provide ambient-assisted living system. They selected robust features from different sensors followed by a two-phase feature selection process to reduce the number of features. Moreover, multiple classification models were trained and tested to increase the accuracy of DLD. Five different datasets have been utilized to test the system performance, which shows that multi-sensors datasets, such as mHealth and FSP, had better results than single sensor-based datasets. However, more sensor positions with unsupervised learning methods must be added to increase the detection rate.

Ali *et al.* [26] proposed a ubiquitous solution for healthcare monitoring by using multi-sensors, social networking data, and machine learning techniques. They also recommended a procedure that works to ensure regular results for long-term usage. Their proposed method suggested a different layered architecture for processing data. Initially, they utilized data sources, data collection, and data storage layers to handle a large number of varying records. Then, they used the analytics engine layer to pre-analyze data, pre-process data, extract features, and reduce the number of features. Finally, they employed data classification and data presentation layers. However, while the experimental results showed good accuracy for drug side effects, the method misclassified the mental health, blood pressure, and diabetes classifications.

Badawi *et al.* [27] proposed a novel method based on the Human Gait Database (HuGaDB) dataset. Their contributions include the identification of the direction and sensor position, the best feature selection method, and achieving good recognition accuracy for HuGaDB. They also recommended an algorithm for sensor fusion and feature selection. Samuel *et al.* [28] suggested using the different time-domain features in order to improve the results of EMG in a body part motion classification. They proposed three new time-domain features: the absolute value of the summation of the square

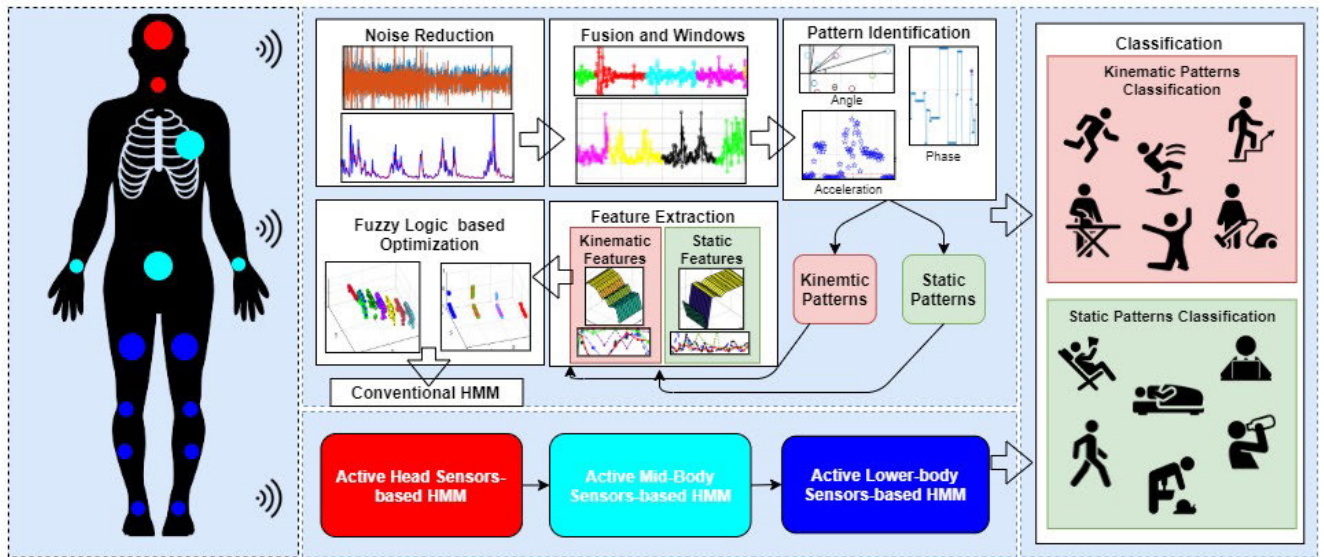


FIGURE 1. Flow architecture of the proposed MS-DLD system.

root, the mean value of the square root, and the absolute value of the summation of the \exp^{th} root from the filtered EMG dataset. Additionally, they utilized LDA and artificial neural network to detect the action patterns. However, the results found that using this method have shown improved effects in categorizing specific body part motion patterns only.

III. PROPOSED MS-DLD SYSTEM

The proposed system detects daily locomotion using body-worn inertial sensors along with other electrophysiology sensors. Primarily, signals acquired from multi-sensors have been filtered through low-pass and high-pass Butterworth filters and a modified WTQ-based filter to eliminate missing values, biasness, and noise. Then, these filtered signals are fused and ordered by a fixed-sliding window for five seconds each. After the pre-processing phase, the kinematic-static energy patterns have been observed to pre-categorize the windowed data into two sets: kinematic patterns and static patterns. The paper describes the features extracted for both the kinematic and static energy patterns separately using a variety of domains comprising entropy, cepstral, and spectral-domains features, which are further scaled via codewords generation for pertinent features selection. Finally, in the proposed MS-DLD technique, a standard HMMs classification method has been implemented on the related features to detect daily locomotion actions. Fig. 1 shows the flow architecture of the proposed MS-DLD system. For the body-specific modified HMMs based method, the proposed technique provides data without any processing to the body-specific modified HMMs and get the kinematic and static energy-based locomotion classified.

A. DATA ACQUISITION AND PRE-PROCESSING

During data acquisition, the acquired signals are gathered from multiple body-worn IMUs and EEG for further analysis.

IMUs are solo units that incorporate accelerometer, gyroscope, and magnetometer sensors. Electrophysiology signals enable monitoring of brain, heart, and muscle-related activities. Sudden fluctuations in locomotion can cause random noise in sensor readings and disturb the signal contours [29]. To sustain the data nature, the proposed system has been used to process the noisy signals with a modified WTQ-based filter for IMUs and a Butterworth denoising filter for electrophysiology signals. The modified WTQ-based filter analyzes the inertial data by filtering the missing values, biasness, and noise to obtain calibrated signals for the accelerometer, gyroscope, and magnetometer in the calibration phase [30].

An error correction phase has been introduced to remove the gravitational errors [31] from the acceleration data, and the Earth's gravitational field has been used to address the transitory fluctuations in the signal. Then, to handle the gyro drift errors in the gyroscope data [32], discrete WTQ mapping [33] and the rate of change have been derived from the gradient descent [34], [35] in order to normalize the gyroscope data. Furthermore, the Earth's magnetic field has been incorporated to remove magnetometer errors. Lastly, the mapping and optimization phase utilized the Quaternions and gradient descent techniques to obtain normalized data. Fig. 2 shows the function of the modified WTQ-based filter and Algorithm 1 describes it in detail.

B. DATA FUSION AND WINDOWING

Our paper utilized the proposed sliding window approach in [9], which consists of splitting the multi-sensors data into a fixed size to analyze the locomotion actions. This method has been found to be effective for recognizing static locomotion (e.g., lying down, picking up an object) and kinematic locomotion actions (e.g., jumping, jogging, falling). Furthermore, the complex locomotion patterns in the UP-Fall [14] (falling forward and falling sideways), IM-WSHA [36]

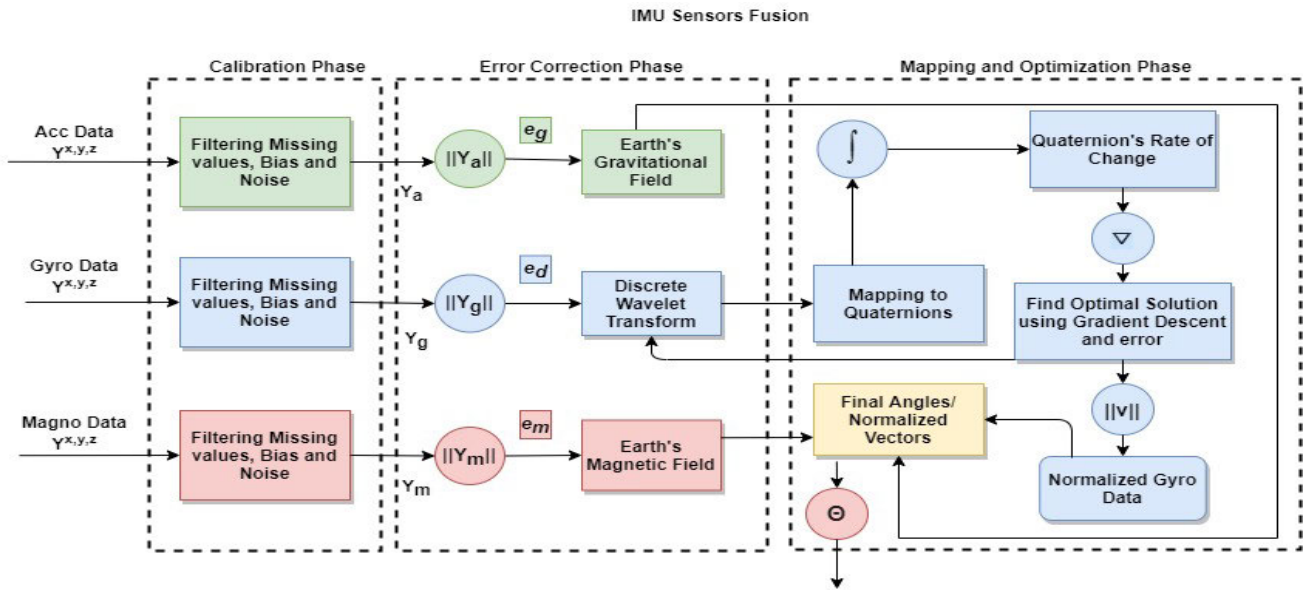


FIGURE 2. Wavelet Transform quaternion-based filter.

Algorithm 1: Wavelet Transform Quaternion-Based IMU Filter

```

Input: acc = acceleration data (x,y,z), gyro = gyroscope data (x,y,z), magno
= magnetometer data (x,y,z), and SR= Sampling Rate
Output: WTQ_filtered_signals = filtered data for IMU signals in MS-DLD
system
WTQ_filtered_signals ← []
error_gravitational ← Acquireerror_gravitational ()
error_magnetic ← Acquireerror_magnetic ()
error_gyro ← Acquireerror_gyro ()
Method: MS-DLD(IMU_WTQF(acc,gyro,mag))
While exit condition not true do
    Filtered_IMU_LPF ← Butterworth_LowPassFilt (acc, gyro, magno)
    Filtered_IMU_HPF ← Butterworth_HighPassFilt (acc, gyro, magno)
    Filtered_IMU_Normalized =
    sqrt(Filtered_IMU_LPF)+sqrt(Filtered_IMU_HPF)
    Gyro_reconstructed =
    WaveletDecomposition(Filtered_IMU_Normalized)
    Gyro_Quaternions_ROC =
    GradientDescent(Quaternion(Gyro_reconstructed))
    Gyro_Normalized = Gyro_reconstructed - Gyro_Quaternions_ROC
    WTQ_filtered_signals ← [Filtered_IMU_Normalized, Gyro_Normalized]
end while
return WTQ_filtered_signals
    
```

(ironing and vacuum cleaning), and ENABL3S [16] (ascending stairs and ascending ramp) dataset activities encompass discontinuities and lurches in indoor-outdoor surroundings. These complexities make it more difficult for the system to sense and detect the activities in negligible time. Thus, a sliding window of five seconds has been introduced to yield better outcomes [13]. Fig. 3 represents the sliding windows for the acceleration signal.

C. KINEMATIC-STATIC ENERGY PATTERNS IDENTIFICATION

In the patterns identification step, the proposed system suggests three different techniques to identify patterns and finally

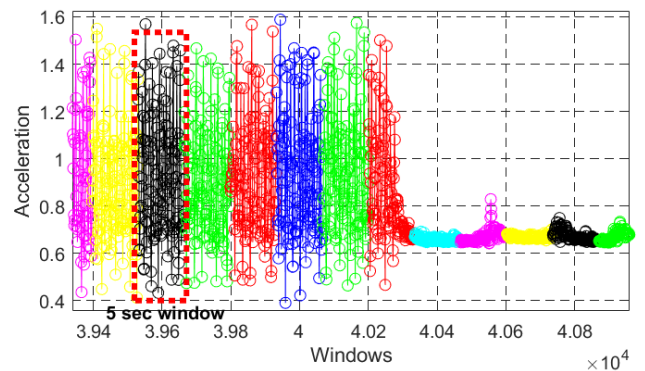


FIGURE 3. Window selection for falling and picking up an object activities from the UP-Fall dataset.

get voted to adopt kinematic or static energy patterns [37] for each locomotion action. First, the acceleration signal has been used to get the difference of minimum and maximum thresholds for an activity. This threshold will help in determining the kinematic and static energy patterns as:

$$V_1(w_n) = \sum_{n=1}^m (\max(w_n) - \min(w_n)) \quad (1)$$

where V_1 is the first vote, w is the windowed signal, and m is the total number of windows for acceleration signal. Next, the acceleration and gyroscope angles [38] are added together to determine the actual angle for an activity to decide the pattern as:

$$V_2(w_n) = \vartheta_n + \varphi_n \quad (2)$$

where V_2 represents the second vote, n is the windowed signal, ϑ is the acceleration angle, and φ is the gyroscope angle. Lastly, phase coherence of whole activity using complex Morlet wavelet [39] has been engaged to detect patterns

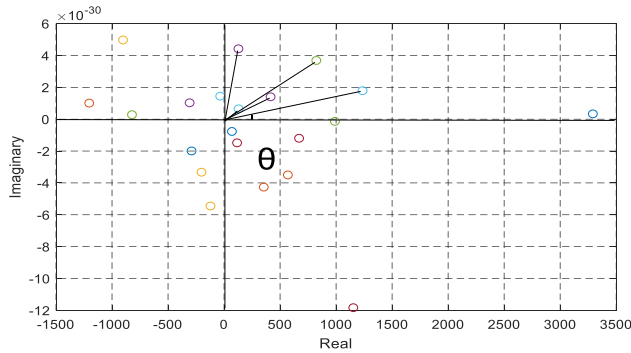


FIGURE 4. Phase angle for kinematic-static patterns identification from EEG.

from the signal as:

$$V_3(w_n) = \frac{\sum_{n=1}^m X(f, t) Y^*(f, t)}{\sqrt{(\sum_{n=1}^m X(f, t) X^*(f, t))(\sum_{n=1}^m Y(f, t) Y^*(f, t))}} \quad (3)$$

where V_3 is the third vote, n is the windowed signal, t is the time series, f is the frequency, and X and Y are the complex signals. Fig. 4 explains the phase angle for EEG data. Then, each of the three techniques has been utilized to identify the vote for kinematic and static energy signals. Hence, the kinematic and static patterns pre-classify locomotion actions into two sets making the final DLD efficient.

D. MULTI-FEATURES EXTRACTION

For the feature extraction, the paper suggested a multi-features model that is comprised of three main areas including entropy, cepstral, and spectral-domains to acquire significant features for both kinematic and static patterns. Algorithm 2 gives a detailed introduction to pattern identification and features extraction.

1) RENYI ENTROPY

Renyi entropy is the generality of Shannon’s entropy and it conserves the additivity of statistically independent systems [40], [41]. It is generally used for the investigation of electrophysiology signals [42]. The formula for the calculation of Shannon entropy and Renyi entropy for the order α is given as:

$$\text{Shannon Entropy } (s) = - \sum_{i=1}^n p_i \log_2 p_i \quad (4)$$

$$\text{Renyi Entropy } (s) = \frac{1}{1 - \alpha} \log_2 \sum_{i=1}^M p_i^\alpha \quad (5)$$

where s is the signal sample values, α is the order = 2, 3, . . . , n , and M is the finite number of possible values from s , and p is the probability of each s . Fig. 5 shows the Renyi entropy of $\alpha = 2$ for the static patterns identified as it has been applied over the static activities identified.

Algorithm 2: Pattern Identification and Multi-Features Extraction

```

Input: WTQ_filtered_signals, eeg_data
Output: patterns and feature vector for LTs in DLD system using patterns
feature_vector_static ← []
feature_vector_kinetic ← []
static_patterns ← []
kinetic_patterns ← []
Method: DLD(Features(WTQ_filtered_signals, eeg_data))
Multi-FeatureVector ← []
EEG_filtered_signals ← Butterworth(eeg_data)
static_patterns ← (EEG_filtered_signals, WTQ_filtered_signals)
kinetic_patterns ← (EEG_filtered_signals, WTQ_filtered_signals)
While exit condition not true do
Entropy_features_static ← ExtractEntropyFeatures(static_patterns)
Entropy_features_kinetic ← ExtractEntropyFeatures(kinetic_patterns)
Spectral_features_static ← ExtractSpectralFeatures(static_patterns)
Spectral_features_kinetic ← ExtractSpectralFeatures(kinetic_patterns)
Cepstral_features_static ← ExtractCepstralFeatures(static_patterns)
Cepstral_features_kinetic ← ExtractCepstralFeatures(kinetic_patterns)
feature_vector_static ← [Entropy_features_static, Spectral_features_static, Cepstral_features_static]
feature_vector_kinetic ← [Entropy_features_kinetic, Spectral_features_kinetic, Cepstral_features_kinetic]
end while
return feature_vector_static, feature_vector_kinetic
    
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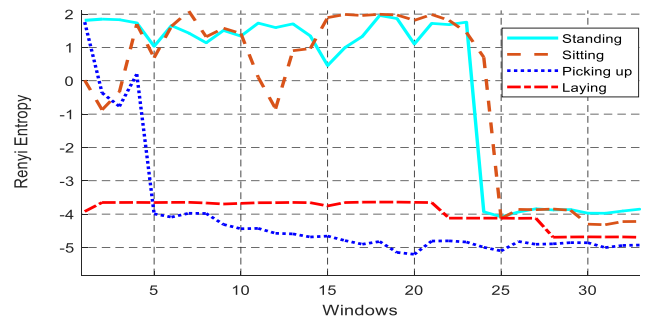


FIGURE 5. Renyi entropy for standing, sitting, picking up an object, and laying locomotion actions.

2) SPECTRAL FLUX

Spectral flux (SF) [43] measures the rate with which the power spectrum of a signal changes. The power spectrum from one window has been compared with the power spectrum from a preceding window of the signal. It is a crucial feature not only in kinematic patterns but also in static patterns. For the proposed system, we have applied SF over static features. SF can be calculated as:

$$SF_{(i,i-1)} = \sum_{k=1}^{WL} EN_i(k) - EN_{i-1}(k) \quad (6)$$

where i represents window number, WL means window length, k is the signal record, and EN shows the normalized discrete Fourier transform coefficient. Fig. 6 describes the SF applied on static patterned activity signals.

3) SPECTRAL ROLLOFF

Spectral rolloff is that point in frequency below which the maximum percentage of the total spectral energy lies.

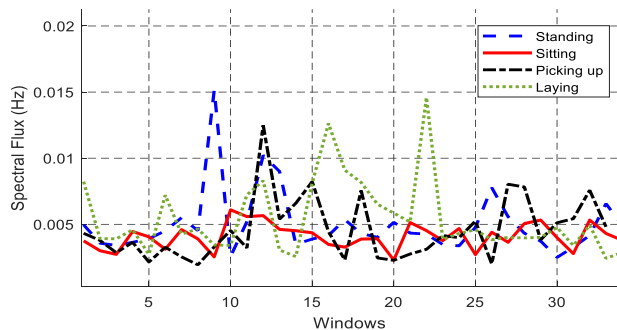


FIGURE 6. Spectral flux for the static signal patterns using the UP-Fall dataset.

It provides a relationship between a signal’s energy and its frequency [44]. We have utilized spectral rolloff for both kinematic and static activities in our system. Spectral rolloff can be calculated as:

$$\arg \min_{fr \in \{1, 2, \dots, N\}} \sum_{k=1}^{fr} PS_k \geq K \sum_{k=1}^N PS_k \quad (7)$$

where n is the frequency range, fr is the spectral rolloff frequency that has been accumulated by a specified proportion k , N is the total number of frequency ranges, and PS_k is the corresponding spectral magnitude. Fig. 7 represents the spectral rolloff points for both static and kinematic identified activities over the IM-WSHA dataset.

4) MEL FREQUENCY CEPSTRAL COEFFICIENTS

Mel Frequency Cepstral Coefficients (MFCCs) are generally used in speech synthesis systems [45]. They largely emphasize speech resolution for lower scales. This work adapted the MFCCs feature extraction approach to identify kinematic patterned data. Primarily, all the signals acquired from multi-sensors are pre-processed using the pre-emphasis with $\alpha = 0.97$. By setting an analysis frame duration of 3000 ms and a frameshift of 10 ms, the kinematic patterned signal is then windowed using hamming and N as 256. Afterward, the discrete Fourier transform (DFT) of the frame has been taken as:

$$S_i(k) = \sum_{n=1}^N s_i(n) h(n) e^{-j2\pi kn/N}, \quad 1 \leq k \leq K \quad (8)$$

where $h(n)$ is an N sample long analysis window, K is the length of DFT, and $s_i(n)$ is the periodogram-based power spectral estimate for the frame.

Meanwhile, Mel filtering, natural logarithm, and discrete cosine transform have been used (See Fig. 8), with the number of Mel filter-bank channels being 20, the number of cepstral coefficients being 12, and the liftering parameter being 22.

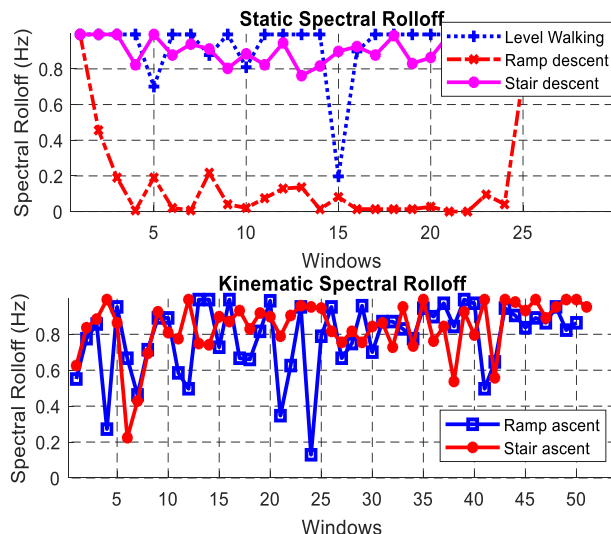


FIGURE 7. Spectral rolloff points for static and kinematic signal patterns using the IM-WSHA dataset.

The filter-banks are created as:

$$H_m(k) = \begin{cases} 0 & k < f(m-1) \\ & \wedge k > f(m+1) \\ \frac{k - f(m-1)}{f(m) - f(m-1)} & f(m-1) \leq k \leq f(m) \\ \frac{f(m+1) - k}{f(m+1) - f(m)} & f(m) \leq k \leq f(m+1) \end{cases} \quad (9)$$

where m is the number of filters and (f) is the list of $m + 2$ Mel-spaced frequencies. However, in order to calculate the 12 cepstral coefficients, the following formula has been applied:

$$d_t = \frac{\sum_{n=1}^N n(c_{t+n} - c_{t-n})}{2 \sum_{n=1}^N n^2} \quad (10)$$

where d_t is the coefficient from the t frame, and a typical value for N is 2. Fig. 8 represents a few results of MFCCs for different activities.

5) FUZZY ENTROPY

Fuzzy entropy has been used as a negative natural logarithm of the conditional probability in which two vectors with the same m points remain similar for $m + 1$ points [46]. Fuzzy entropy is used to measure ambiguity in locomotion actions. Furthermore, the regularity of time series more efficiently and has been used to differentiate between changes in kinematic locomotion in indoor-outdoor environments as:

$$\begin{aligned} \varphi^m(n, r) &= \frac{1}{N - m} \times \sum_{i=1}^{N-m} \left(\frac{1}{N - m - 1} \right) \sum_{j=1, j \neq i}^{N-m} D_{ij}^m \quad (11) \end{aligned}$$

$$\begin{aligned} \varphi^{m+1}(n, r) &= \frac{1}{N - m} \times \sum_{i=1}^{N-m} \left(\frac{1}{N - m - 1} \right) \sum_{j=1, j \neq i}^{N-m} D_{ij}^{m+1} \quad (12) \end{aligned}$$

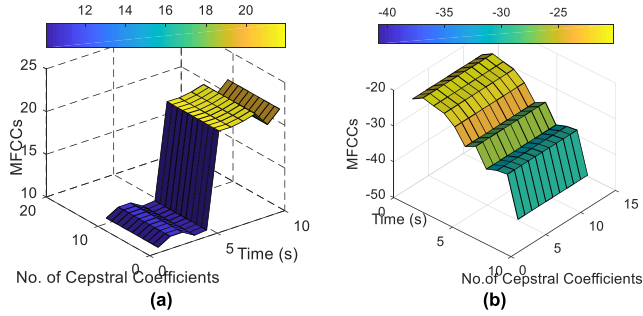


FIGURE 8. MFCC applied to kinematic pattern activities of (a) falling forward using hands and (b) falling backward.

$$Fuzz\ Entro(m, n, r, N) = \ln\phi^m(n, r) - \ln\phi^{m+1}(n, r) \quad (13)$$

where m is the consecutive vector sequence, n is the gradient, r is the width of exponential function boundary, N is the sample, and D_{ij}^m is the similarity measure. Different values of n and r have been applied to the kinematic locomotion signals and $r = 0.24$ along with $n = 0.2$ have been selected for all the windowed kinematic signals as shown in Fig. 9.

6) LINEAR PREDICTION CEPSTRAL COEFFICIENTS

Linear prediction cepstral coefficients (LPCCs) can be used to separate the excitation signal and the transfer function [47]. The cepstrum can show a rate of change for different spectrum bands. Linear prediction coefficients are converted into LPCCs c_n using the recursive relation between the predictor coefficients and the cepstral coefficients as:

$$C_o = \ln\sigma^2 \quad (14)$$

$$c_m = a_m + \sum_{n=1}^{m-1} \binom{n}{m} c_n a_{m-n}, \quad 1 \leq m \leq p \quad (15)$$

$$c_m = \sum_{n=1}^{m-1} \binom{n}{m} c_n a_{m-n}, \quad p \leq m \leq d \quad (16)$$

where σ^2 is the gain in LP analysis, d is the number of LPCCs, and a_m is the linear prediction coefficient. Fig. 10 gives details about multiple static patterned activity signals for the ENABL3S dataset.

E. CODEWORDS GENERATION USING FUZZY LOGIC BASED OPTIMIZATION

For the codewords generation of the extracted kinematic-static multi-features, the MS-DLD system proposes utilizing fuzzy logic-based optimization. First, the system identifies input and output variables and decides descriptors, i.e. linguistic or numerical followed by triangular membership functions definition for each input and output variable as:

$$f(x : l, m, n) = \max\left(\min\left(\frac{x-l}{m-l}, \frac{n-x}{n-m}\right), 0\right) \quad (17)$$

where x represents the input variable and $l, m,$ and n are the parameters for triangular shape. Then, a rule base has been defined and rule evaluation has been done using the

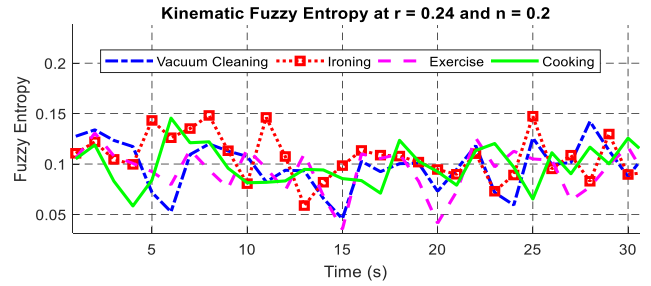


FIGURE 9. Fuzzy entropy for irregularity detection in five kinematic locomotion actions for the IM-WSHA dataset.

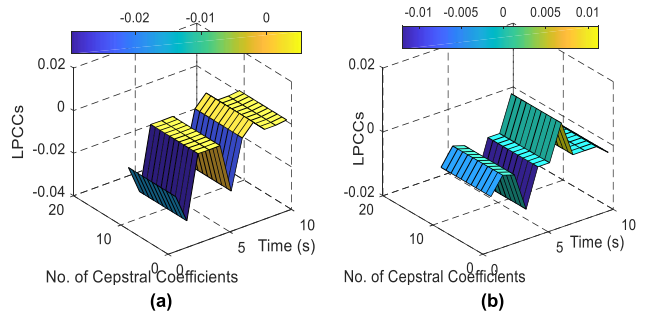


FIGURE 10. LPCCs for (a) ramp descent and (b) stair descent activities in ENABL3S dataset.

triangular membership function. Lastly, defuzzification has been done on the data by taking the minimum of each feature and then the maximum of all the features [48]. Lastly, the system provides optimized multi-features codewords vector symbolized in Fig. 11.

F. DAILY LOCOMOTION DETECTION USING HIDDEN MARKOV MODELS

After reducing the multi-features vector to codewords, the standard MS-DLD system proposes applying HMMs for each activity. HMMs are the statistical models containing finite states that are used to depict the transition and emission probabilities. Multiple parameters are related to HMMs such as states, events sequence, transition matrix, emission matrix, and prior. All these parameters are set to train each locomotion action using HMMs and the likelihood of the sequence of the events has been calculated as:

$$P(X | Q, \omega) = \prod_{n=1}^N P(x_n | q_n, \omega) = b_{q_1, x_1} \cdot b_{q_1, x_1} \dots b_{q_1, x_1} \quad (18)$$

$$P(X | \omega) = \sum_{allQ} P(X, Q | \omega) \quad (19)$$

where X represents the event sequences x, ω are the parameters described above, b is the emission probability and Q is all the possible event sequences q . One HMM has been trained for each kinematic and static patterned activity over all three datasets. A k-fold cross-validation technique has been applied to get training and testing data, where $k = 10$. Algorithm 3 explains the process of HMMs training for each kinematic locomotion.

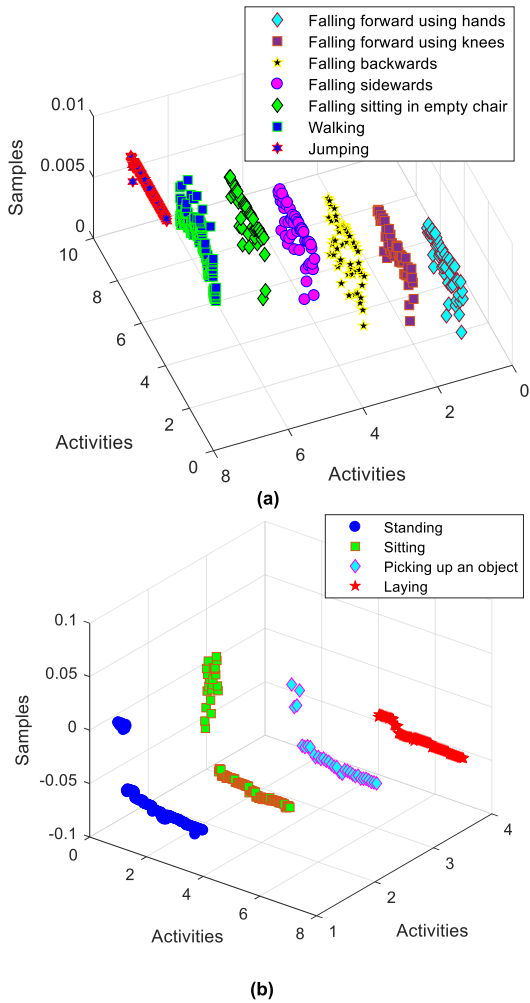


FIGURE 11. Fuzzy logic-based optimization for (a) kinematic locomotion and (b) static locomotion actions using UP-Fall dataset.

For body-specific modified HMMs, raw data from multi-sensors has been provided to HMMs. The proposed method divides the HMMs into three body-related sensors placement, namely, active head, active mid-body, and active lower-body sensors. The active head includes all the sensors placed on the head and neck. Active mid-body contains all the sensors placed from shoulders to waist. Lastly, the active lower body comprises all the sensors attached from thighs to feet. Fig. 12 illustrates the concept of body-specific modified HMMs over the UP-Fall dataset. Active head HMM has the EEG and neck-specific IMU, active mid-body HMM comprises of wrist, waist, and pocket IMUs, whereas, active lower-body consists of ankle IMU data. The raw data from the multi-sensors have been given to these three body-specific modified HMMs in the mentioned body-part order and further, the three HMMs provide log-likelihoods for each locomotion detection.

IV. EXPERIMENTAL SETTINGS AND ANALYSIS

All experiments have been performed on a laptop equipped with Intel Core i7-8550U 1.80GHz processing power,

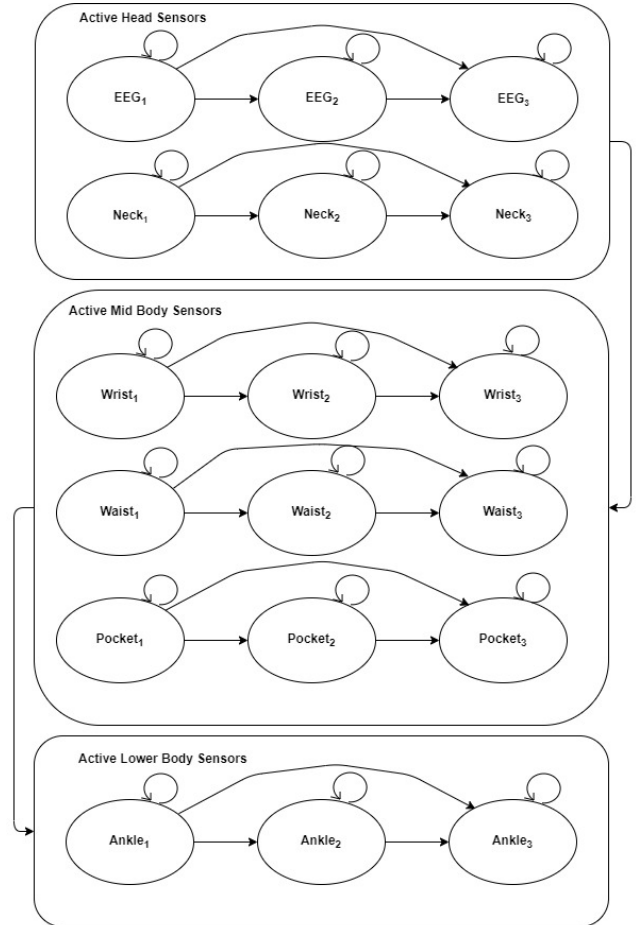


FIGURE 12. Architecture diagram for body-specific sensors based modified HMMs.

24GB RAM having x64 based Windows 10, and MATLAB tool. Moreover, a platform has been set to assess the performance of the proposed method MS-DLD accomplished on three datasets, namely, UP-Fall, IM-WSHA, and ENABL3S benchmark datasets. To detect the validation performance of the MS-DLD systems for different circumstances, the k-fold cross-validation technique has been utilized.

A. UP-FALL DATASET

The benchmark dataset named UP-Fall [14] has been made using five IMUs and an EEG headset to gather 11 different daily locomotion actions performed by 17 subjects. The performed locomotion include both kinematic and static activities such as *falling forward using hands, falling forward using knees, falling backward, falling sideward, falling sitting in the empty chair, walking, standing, sitting, picking up an object, jumping, and laying.*

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

The second selected dataset is IM-WSHA [15] that has been made using three IMUs placed at the chest, thigh, and wrist

Algorithm 3: Training HMMs for Each Kinematic Locomotion

```

Input: Optimized Multi-features codewords
Output: L: Detected daily Locomotion
Method:  $em_i$  = emission matrix,  $tm_i$  = transition matrix
symbols = daily locomotion, state =  $\{s_1, s_2, \dots, s_n\}$ 
sequence = locomotion data, previous_locomotion_LL = 0
while (codewords)
    Mu = mean(sequence);
    Cov = covariance(sequence);
    P = state_transition_matrix(sequence);
    Pi = priors(sequence);
    LL = log_likelihood(sequence);
    if LL > previous_locomotion_LL, then L = LL and
        previous_locomotion_LL = LL;
end
return L
    
```

to capture daily locomotion in real-time. The kinematic-static locomotion has been performed by 10 subjects in the smart home environment including, *phone conversation, vacuum cleaning, watching TV, using computer, reading books, ironing, walking, exercise, cooking, drinking, and brushing hair.*

C. ENCYCLOPEDIA OF ABLE-BODIED BILATERAL LOWER LIMB LOCOMOTOR SIGNALS (ENABL3S) DATASET

The last benchmark ENABL3S dataset [16] has been taken from the synchronized capturing system of four IMUs placed at both wrists and shanks along with four EMGs placed at both biceps and thighs. A group of 16 volunteers was asked to execute a set of five locomotion actions three times each. The locomotion includes *stand still, squat and stand up, jump, raise right hand, and jogging.*

D. MS-DLD EVALUATION VIA EXPERIMENTAL RESULTS

We have evaluated the performance of the standard MS-DLD system having patterns identification, multi-features, fuzzy logic optimization, and HMMs along with body-specific modified HMMs system over the UP-Fall, IM-WSHA, and ENABL3S datasets.

The experiments have been repeated three times to accurately evaluate the performance of the proposed systems. Tables 1 and 2 illustrate the confusion matrices for kinematic locomotion and static locomotion detection over the UP-Fall dataset achieving 90.0% and 87.5% mean accuracies, respectively. Tables 3 and 4 depict the mean detection rate of 86.0% for kinematic locomotion and 88.3% for static locomotion over the IM-WSHA dataset. Tables 5 and 6 represent the confusion matrices for kinematic and static locomotion over the ENABL3S dataset showing the mean accuracies of 86.7% and 90.0%, respectively.

Tables 7-9 presents the confusion matrices for the body-specific-sensors-based modified HMMs system showing kinematic patterned locomotion actions over the UP-Fall, IM-WSHA, and ENABL3S datasets, respectively. Similarly, Tables 10-12 demonstrate the confusion matrices for the results of body-specific-sensors-based modified

TABLE 1. Confusion matrix for kinematic locomotion over the UP-Fall dataset using standard HMMs.

Locomotion actions	FFH	FFK	FB	FS	FSC	WK	JP
FFH	10	0	0	0	0	0	0
FFK	0	9	1	0	0	0	0
FB	0	0	8	0	2	0	0
FS	0	1	0	9	0	0	0
FSC	0	0	0	1	8	1	0
WK	0	0	1	0	0	9	0
JP	0	0	0	0	0	0	10

Mean detection rate = 90.0%

*FFH = falling forward using hands; FFK = falling forward using knees; FB = falling backward; FS = falling sideward; FSC = falling sitting in empty chair; WK = walking; JP = jumping

TABLE 2. Confusion matrix for static locomotion over the UP-Fall dataset using standard HMMs.

Locomotion actions	standing	sitting	picking up an object	laying
standing	10	0	0	0
sitting	0	8	1	1
picking up an object	0	1	8	1
laying	0	1	0	9

Mean detection rate = 87.5%

TABLE 3. Confusion matrix for kinematic locomotion over the IM-WSHA dataset using standard HMMs.

Locomotion actions	vacuum cleaning	ironing	walking	exercise	cooking
vacuum cleaning	9	1	0	0	0
ironing	0	9	0	1	0
walking	1	0	8	0	1
exercise	1	0	0	9	0
cooking	0	1	0	1	8

Mean detection rate = 86.0%

HMMs system showing static patterned locomotion actions over the UP-Fall, IM-WSHA, and ENABL3S datasets, respectively. The mean detection rates of 94.30%, 92.0%, and 90.0% have been achieved for kinematic locomotion detection and 95.0%, 93.3%, and 95.0% have been presented for the static locomotion detection over UP-Fall, IM-WSHA, and ENABL3S datasets, respectively.

Tables 13 and 14 evaluates the performance of conventional MS-DLD system using micro precision, micro recall, and micro F1-score measures over the selected datasets. The micro-averaged F1-score shows promising results of the proposed system as it combines the precision and recall measures

TABLE 4. Confusion matrix for static locomotion over the IM-WSHA dataset using standard HMMs.

Locomotion actions	PC	WT	UC	RB	DR	BH
PC	9	0	0	0	0	1
WT	0	9	1	0	0	0
UC	0	1	9	0	0	0
RB	0	0	0	10	0	0
DR	1	0	0	0	8	1
BH	1	0	0	1	0	8
Mean detection rate = 88.3%						

PC = phone conversation; WT = watching TV; UC = using computer; RB = reading books; DR = drinking; BH = brushing hair

TABLE 5. Confusion matrix for kinematic locomotion over the ENABL3S dataset using standard HMMs.

Locomotion actions	squat and stand up	jump	jogging
squat and stand up	9	1	0
jump	0	9	1
jogging	1	1	8
Mean detection rate = 86.7%			

TABLE 6. Confusion matrix for static locomotion over the ENABL3S dataset using standard HMMs.

Locomotion actions	stand still	raise right hand
stand still	9	1
raise right hand	1	9
Mean detection rate = 90.0%		

into a single one. Table 15 presents the comparison outcomes between proposed MS-DLD systems and the other existing methods. It is clear from the comparison that the proposed body-specific-based modified HMMs system achieved better mean accuracy than standard MS-DLD system and other state-of-the-art methodologies in literature.

V. DISCUSSIONS

The MS-DLD systems have been explained using the fused multi-sensors data to achieve maximum accuracy. For the standard detection system, we proposed the modified WTQ-based filter for IMU data pre-processing. The system further identifies the kinematic and static locomotion patterns from windowed data and extracts features separately for both pattern types in multiple domains. Furthermore, codewords have been extracted and one HMM has been utilized to classify each locomotion action. For the second approach, conventional system has been improved and modified HMMs for sensors placed on different body-specific parts have been

TABLE 7. Confusion matrix for kinematic locomotion over the UP-Fall dataset using body-specific modified HMMs.

Locomotion actions	FFH	FFK	FB	FS	FSC	WK	JP
FFH	10	0	0	0	0	0	0
FFK	0	9	0	1	0	0	0
FB	0	0	9	1	0	0	0
FS	0	0	0	10	0	0	0
FSC	0	1	0	0	9	0	0
WK	0	0	0	0	0	10	0
JP	0	1	0	0	0	0	9
Mean detection rate = 94.3%							

*FFH = falling forward using hands; FFK = falling forward using knees; FB = falling backward; FS = falling sideward; FSC = falling sitting in empty chair; WK = walking; JP = jumping

TABLE 8. Confusion matrix for kinematic locomotion over the IM-WSHA dataset using body-specific modified HMMs.

Locomotion actions	vacuum cleaning	ironing	walking	exercise	cooking
vacuum cleaning	9	1	0	0	0
ironing	1	9	0	0	0
walking	0	0	10	0	0
exercise	0	0	1	9	0
cooking	0	1	0	0	9
MEAN DETECTION RATE = 92.0%					

TABLE 9. Confusion matrix for kinematic locomotion over the ENABL3S dataset using body-specific modified HMMs.

Locomotion actions	squat and stand up	jump	jogging
squat and stand up	10	0	0
jump	1	9	0
jogging	1	1	8
Mean detection rate = 90.0%			

proposed. The multi-sensors signals have been taken purely without any processing and the results achieved are better than those of the conventional approaches.

Multiple techniques have been computed to select the most effective ones in the proposed standard system. For the calibration of acceleration signal in WTQ-based filter, we have tried and tested both minimum and average gravity removal techniques. The average gravity removed from acceleration data provided with more accurate results. Similarly, a hyper-parameter for gradient descent known as learning rate, in the WTQ-filter for IMUs, has been tested over multiple values and 0.01 has been selected as the most effective learning rate.

TABLE 10. Confusion matrix for static locomotion over the UP-Fall dataset using body-specific modified HMMs.

Locomotion actions	standing	sitting	picking up an object	laying
standing	10	0	0	0
sitting	0	9	0	1
picking up an object	0	1	9	0
laying	0	0	0	10
Mean detection rate = 95.0%				

TABLE 11. Confusion matrix for static locomotion over the IM-WSHA dataset using body-specific modified HMMs.

Locomotion actions	PC	WT	UC	RB	DR	BH
PC	9	0	0	1	0	0
WT	0	9	1	0	0	0
UC	0	0	10	0	0	0
RB	0	0	0	9	0	1
DR	0	0	0	0	10	0
BH	1	0	0	0	0	9
Mean detection rate = 93.3%						

*PC = phone conversation; WT = watching TV; UC = using computer; RB = reading books; DR = drinking; BH = brushing hair

TABLE 12. Confusion matrix for static locomotion over the ENABL3S dataset using body-specific modified HMMs.

Locomotion actions	stand still	raise right hand
stand still	10	0
raise right hand	1	9
Mean detection rate = 95.0%		

TABLE 13. Performance evaluation for standard MS-DLD system.

Dataset	Locomotion Class (Dataset)	Micro Precision	Micro Recall	Micro F1
UP-Fall	Kinematic	0.90	0.90	0.90
	Static	0.87	0.87	0.87
IM-WSHA	Kinematic	0.86	0.86	0.86
	Static	0.88	0.88	0.88
ENABL3S	Kinematic	0.87	0.87	0.87
	Static	0.90	0.90	0.90

Our proposed method did not rely upon one technique for the patterns identification stage and suggested three types of techniques, such as acceleration threshold, phase angle, and phase coherence. These three techniques have been utilized to

TABLE 14. Performance evaluation for state-of-the-art MS-DLD system.

Dataset	Locomotion Class (Dataset)	Micro Precision	Micro Recall	Micro F1
UP-Fall	Kinematic	0.94	0.94	0.94
	Static	0.95	0.95	0.95
IM-WSHA	Kinematic	0.92	0.92	0.92
	Static	0.93	0.93	0.93
ENABL3S	Kinematic	0.90	0.90	0.90
	Static	0.95	0.95	0.95

TABLE 15. Comparison of detection accuracy for MS-DLD system with other state-of-the-art systems over the UP-Fall, IM-WSHA, and ENABL3S datasets.

Methods	UP-Fall (%)	IM-WSHA (%)	ENABL3S (%)
RPLB + Adagrad system [8]	-	81.73	-
RPLB + Stochastic Gradient Descent system [8]	-	83.18	-
Genetic algorithm based system [15]	-	81.92	-
SVM based IMU+EEG system [14]	90.77	-	-
MLP based modal system [43]	93.33	-	-
LDA based classification system [49]	-	-	85.78
CNN based classification system [49]	-	-	90.93
Proposed MS-DLD system mean accuracy	88.75	87.15	88.35
Proposed body-specific HMMs based system mean accuracy	94.65	92.65	92.50

vote for the decision between kinematic and static patterned signals. Multiple feature extraction techniques have been calculated to decide upon the chosen ones including time, frequency, entropy, spectral, and cepstral domains. Similarly, the fuzzy logic based optimization has been found to be better performing when compared to other features optimization or selection techniques such as LDA and sequential forward selection.

The proposed system has limitations as described below:

- Combining the multiple types of sensors gives favorable results. However, it can cause problems related to the robustness and accuracy of a single sensor.
- The proposed MS-DLD systems have been applied to limited sensors. However, they can provide diverse results for other types of sensors.
- The results for the standard approach can be improved by exploring other domains of features and optimization techniques for locomotion patterned actions.

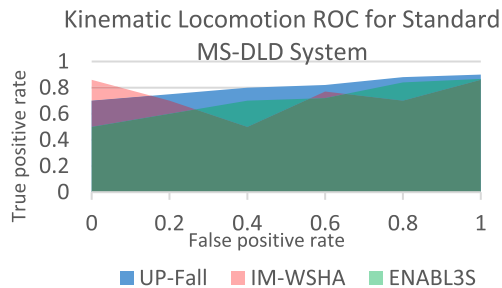


FIGURE 13. ROC for UP-Fall, IM-WSHA, and ENABL3S datasets.

- Our proposed system can detect the limited daily locomotion actions. Conversely, there can be locomotion patterns that standard MS-DLD system has not been trained to detect such as playing games, sports activities, and other body movements.
- The proposed methodologies have shown promising outcomes for the accuracy and F1-score performance monitoring parameters. However, if we look at the receiver operating characteristic (ROC) curve over the multiple discussed datasets, we can see the shortcomings of the system via area under the curve (AUC). Fig. 13 represents the ROC and AUC for UP-Fall, IM-WSHA, and ENABL3S datasets.

By looking at the experimental results, we accomplish that the proposed body-specific modified HMMs approach has better results as compared to the conventional systems. Moreover, the locomotion patterns and multi-features computed from IMUs and biosensors increased the detection accuracy of the standard proposed system when compared to the existing methods.

VI. CONCLUSION AND FUTURE WORK

In this paper, a standard MS-DLD system has been proposed, which is based on multi-features including Renyi entropy, SF, MFCCs, spectral rolloff, Fuzzy entropy, and LPCCs. Kinematic and static locomotion patterns have been identified using three characteristics, namely, phase coherence, acceleration threshold, and phase angle, which deeply analyzed the signals' contours. Features have been optimized by fuzzy logic technique and locomotion actions have been classified via HMMs to improve the DLD via body-worn multi-sensors. In addition, the paper proposed a body-specific modified HMMs based system focusing on the active head, mid-body, and lower body sensors placement and compared the performance of conventional systems with the proposed modified system. The novelties of our proposed systems include the kinematic-static patterns identification, WTQ-filter for IMU signals, and active body-specific-sensors-based HMMs for classification. Three benchmark datasets including UP-Fall, IM-WSHA, and ENABL3S have been used during the experimentation phase. The results proved that the proposed systems can significantly enhance the detection rate of locomotion actions. The conventional system achieved mean

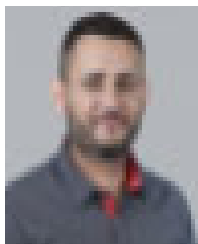
accuracies of 87.57% for kinematic patterns and 88.6% for static patterns over the multiple locomotion in three selected datasets. However, the body-specific modified HMMs based system achieved mean accuracies of 92.1% for kinematic patterns and 94.43% for static patterns over the three datasets.

There are some open challenges for this study, such as limited environment experiments and restricted locomotion detection. In the future, we plan to introduce more variety of locomotion from different environments such as smart environments, healthcare facilities, and sports complexes into our system via multiple types of sensors. To improve the efficacy of proposed research, further experiments are required in the pattern identification methods for multiple sensors. As the system has limited application to DLD situations, therefore new experiments will also be conducted to focus on the promising aspects and deficiencies of the proposed MS-DLD systems.

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