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Wearable Sensors for Evaluation Over Smart Home Using Sequential Minimization Optimization-based Random Forest

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Abstract

In our everyday life records, human activity identification utilizing MotionNode sensors is becoming more and more prominent. A difficult issue in ubiquitous computing and HCI is providing reliable data on human actions and behaviors. In this study, we put forward a practical methodology for incorporating statistical data into Sequential Minimization Optimization-based random forests. In order to extract useful features, we first prepared a 1-Dimensional Hadamard transform wavelet and a 1-Dimensional Local Binary Pattern-dependent extraction technique. Over two benchmark datasets, the University of Southern California-Human Activities Dataset, and the IM-Sporting Behaviors datasets, we employed sequential minimum optimization together with Random Forest to classify activities. Experimental findings demonstrate that our suggested model may successfully be utilized to identify strong human actions for matters related to efficiency and accuracy, and may challenge with existing cutting-edge approaches.

Keywords: Sequential Minimization Optimization, Wearable sensors, 1D Local Binary Pattern, Gait Analysis.

1. Introduction

Gait analysis with wearable sensors is now a highly popular area of study in ubiquitous computing [1] and HCI [2] due to the variety of disciplines in which it may be used, including survey systems, expert systems, sports support, and security surveillance. Real-time bodily activity tracking is currently feasible because to the quick improvements in sensor technology. Human activity sensors are designed to quickly offer details on a person's behavior such that sensing frameworks may quickly assist the users. These sensing frameworks are undoubtedly employed in industrialized technologies including GPS [3] tracking, fitness tracking systems, pedestrian movement tracking, gait analysis, and heart rate monitoring. With all of these industrialized technologies, the systems assist in keeping track of everyday activities and work to enhance the standard of living for people.

Users of body sensor-based systems must wear or carry certain gadgets, such as cell phones and wearable sensing devices. Inertial sensors are used by these body-mounted sensors to collect activity data. Wearable sensors, which consist of IMU sensors [4] like magnetometers, accelerometers and gyroscopes, provide additional degrees of freedom for a complete motion analysis. On the contrary, these sensors use lesser power and pose less confidential risks while in use. A lot of research is being done to build daily life logs and medicine services with an appropriate degree of activity recognition. Numerous studies used various feature extraction techniques to categorize dynamic human activity patterns. One such example is the "Human movement recognition utilizing a wearable wireless dependent approach" [5] described by Dua et al. The USC-HAD dataset's activities are used in our suggested system. Preprocessing, statistical feature analysis and sequential minimal optimization (SMO) [6] along with random forest-dependent feature classification are the three categories used to classify the sports activities from the IM-Sporting Behaviours dataset [7] (soccer, tennis and cricket etc) and (jumping up and down, running in the front direction, moving in an elevator upwards and downwards, etc.). The Gaussian filter and median filter are two of the first preprocessing filters used on raw signal data. To extract special characteristics from the raw data like 1-D Walsh Hadamard transform (WHT) [8], mean, variance, peak-magnitude to RMS ratio, and 1-D Local Binary Pattern, the pre-processed data is additionally processed. Afterward, the obtained features are merged to form feature vectors. Finally, resulting vectors for various physical activities are injected across the SMO pre-classifier along with the Random Forest (RF) approach.

The later parts of this paper are categorized into the following sections: Section II presents the Literature Review; Section III exhibits the proposed system's detailed architecture, including denoising, feature extraction, and recognition. Section IV provides insight into implementation dataset outcomes and discusses classifier output. In Section V, the conclusion is presented.

2. Literature survey

Tahir et al. [9] in 2020 showed that in order to support seniors' independence and comfort, wearable sensors are becoming more widely recognized in healthcare. In this research, we provide a model for recognizing human activity using signal data from motion node sensors, such as gyroscopes and accelerometers, which are known as inertial sensors. To evaluate lower/upper cutoff frequency characteristics, the inertial data are first processed using a variety of filters, including median, and Hampel filters [10]. To optimize the occurrence of ideal feature values, it derives a multifaced model for statistical and binary features. Then, in a phase of feature optimization, adaptive moment estimation and AdaDelta are added to adopt learning rate patterns. The maximum entropy Markov model [11] for empirical expectation and greatest entropy, that measures signal variances for outcomes in outperformed accuracy, further processes these optimized patterns. Our model was put through its paces using the USC-HAD [12] as a benchmark dataset and the new self-annotated sports dataset known as Intelligent Media sporting Behaviour (IMSB). The findings beat current popular statistical state-of-the-art approaches by reaching an enhanced identification accuracy of 92.34%, 94.15%, and 91.82% when compared with USC-HAD, IMSB, and M-health datasets, respectively. Bozkurt [13] in 2022 showed that the purpose of this research is to forecast user behaviour using context data collected by sensors like gyroscopes and accelerometers. In order to anticipate activity, the implemented classification algorithms take features from training data and develop a classification model based on the features. The identification of human activities has been explored and contrasted in this study using a variety of traditional machine learning and deep learning approaches. On the publicly accessible UCI-HAR dataset, experimental findings demonstrate that the well-established Deep Neural Network [14] model obtained an accuracy of 93.22% and mean absolute error of 0.04. When compared to other categorization algorithms used in this investigation, our strategy predicted human activity the best.

3. Methodology

This part comprises our suggested recognition model, which covers the preprocessing stage, which is the first step. Fig. 1 depicts the schematic flow of our wide model. We first separated sensor raw data into 30ms-long frames. Before using the data for further processing, we must preprocess it by compensating for the noise. Therefore, Extreme signal peaks are tamed using Gaussian and median filters. The feature extraction component is then used to transmit the accelerometer and gyroscope measurements. It is beneficial to turn denoised data into a group which offers comprehensive non-redundant data. Denoising [15] is then accompanied with feature extraction stages, where Wavelet characteristics such as the Hadamard transform and statistical features like mean, variance, peak magnitude to RMS are utilized. Additionally, from the cleaned data, a 1-D LBP feature is recovered. The SMO pre-classifier receives the feature vectors last. Finally, a RF approach is used in improving the analysis of human behavior.

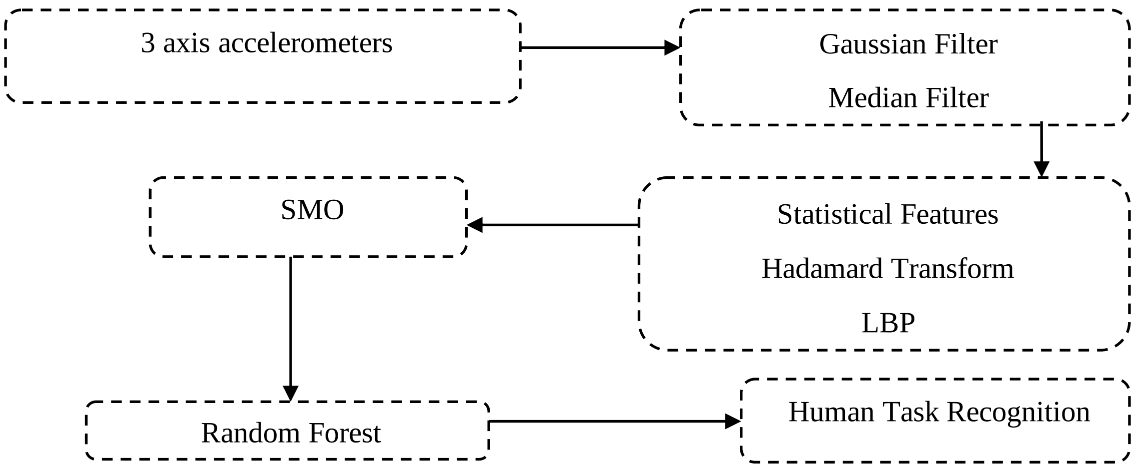

Figure 1. Block schematic for the proposed human activity recognition system

3.1 Processing of raw data and reduction of noise

To improve the signal and simplify the process of recognizing human movement, the Motion Node device data must be analyzed. In our plan, the noisy signal is subjected to Gaussian [16] and median filters. By doing so, the signal is smoothed and outliers are avoided. The median filter is a nonlinear filter used to amplify signals. It works well to remove impulsive noise from a signal. The current homogeneous method for eliminating the roughness components from a primary surface is the Gaussian filter.

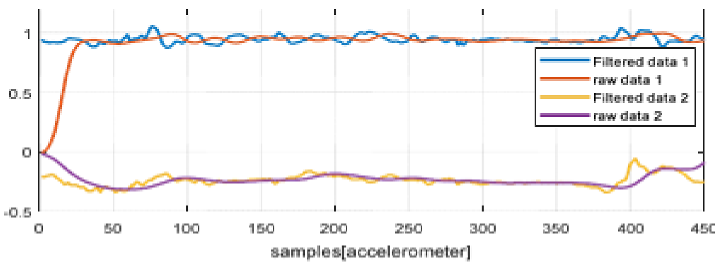

Figure 2. Evaluation of treated and raw signal components

Data from an accelerometer and gyroscope that is both raw and filtered.

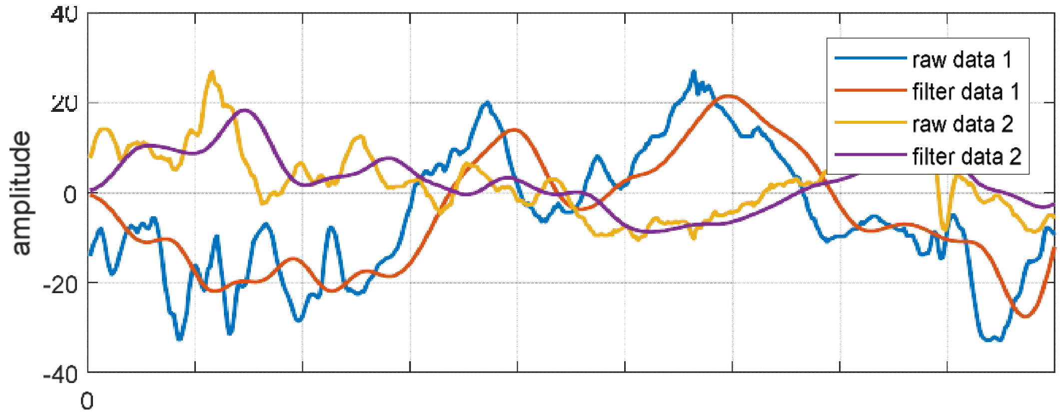

Figure 3. Gyroscope data with several filtered and raw signal components

3.2 Techniques for generation of feature

Here, the authors outline the procedures used to transform signal data into usable information. Wavelet transform, time-frequency transform and frequency transform are just a few of the domains where characteristics may be extracted. Following are explanations of two different types of features: the Hadamard transform and the 1-D LBP.

a. A typical signal features

It is defined as each signal frame's total number of data points divided by the total amount of the denoise data. We determined the mean of the accelerometer and gyroscope signals in our dataset. Each vector's mean is determined as follows:

$$mean(signal) = \sum_{r=1}^{n} \frac{c_1}{M} \tag{1}$$

Here c1 denotes the coefficients and indicates how many overall coefficients there are in the vector. Mean points of the MotionNode sensor [17] are shown in Fig. 3.

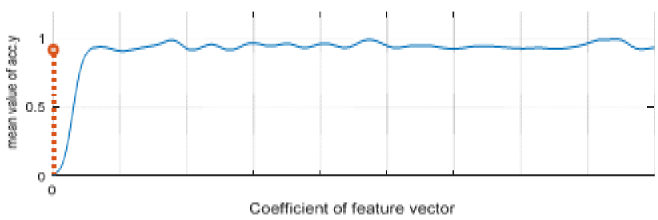

Figure 4. 1-D vector scheme showing the gyroscope's mean readings along the z-axis

b. Signal Variance Feature

It serves as the difference between the instantaneous values' equalized squared sum and the mean value. The variance points of the MotionNode sensor are shown in Fig. 4. Each vector's variance is determined as follows:

$$signal(variance) = \frac{\sum_{a=1}^{n}(Z - Z')^2}{n-1} \quad (2)$$

c. Peak to peak

It may be estimated using the length between both the mean of positive crusts and positive troughs. The authors determined the signals peak to peak for the gyroscope and accelerometer.

d. Peak magnitude- to-RMS ratio

The positive and negative peak evaluations of the single transition waveform were determined using this feature. It may be computed using the equation given as follows:

$$signal(PRMS) = \frac{|A|\infty}{\sqrt{\frac{1}{N}\sum_{n=1}^{N}|A_n|^2}} \quad (3)$$

e. 1-D WHT

A signal is divided into a collection of orthogonal signals also called Walsh functions. It resembles a structure of a rectangular waveform. It has a wide range of uses, including filtering [18], voice processing, analyzing healthcare signals, and differentiating non-linear signals.

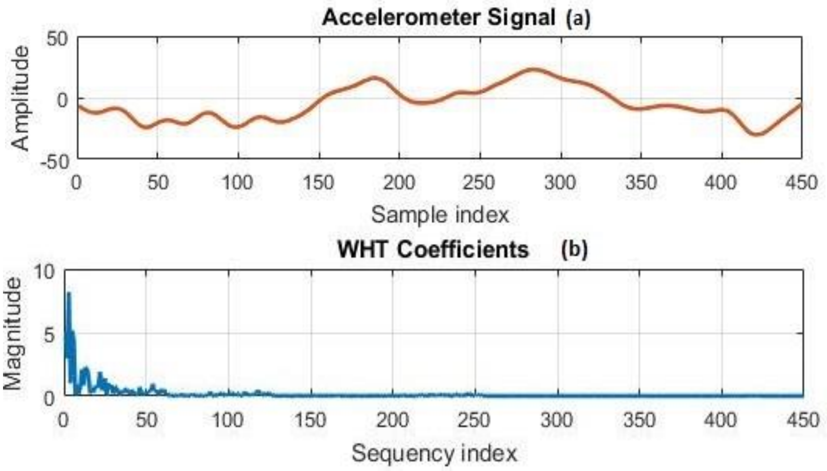

Figure 5. WHT coefficients signals and 1-D WHT signals as (a) vector plots of 1Dimensional WHT signal features and (b) plots of Walsh Hadamard Transform coefficients

f. LBP in 1-D

The most common method for extracting features from photos is local binary patterns. It is mainly utilized in facial recognition. The authors have employed 1-D LBP for 1-D signal data in this work. To identify variations in the signal data that has been processed, a histogram is carefully examined. The 1-D Local Binary Pattern histogram's output exhibits how often certain patterns in the signal occur.

3.3 Categorizing various human actions

To maximize the accuracy of various actions, all characteristics must be further processed by a classifier after feature extraction. A scientific model must be used in order to discriminate between the feature components.

In our tests, we used the SMO algorithm to classify human activities. Utilizing SMO in conjunction with a random forest classifier aims to maximize the signal value for each class. SMO performs better in terms of memory than other classifiers like SVM [19]. Following is an explanation of the SMO and RF [20] model:

a. SMO

A standard SVM loses ground to SMO if the training set is large. For this, SMO offers a cutting-edge approach to Support Vector Machine training. It divides a large programming problem into a series of smaller QPPs. For each round of training, Sequential Minimization Optimization retains a pair of Lagrange multipliers. It resolves every minor QP issue, and then repeats the procedure until it finds a solution to the main QP issue.

Comparing SVM training with SMO's innovative contribution, SVM training results in a space complexity reduction from (n2) to O (1). The barrier, however, continues to be temporal complexity.

We get to the conclusion that SMO considerably increases the scaling training set [21] size in order to refute the aforementioned claim. SVM and SMO are binary classifiers that support multiple classes. However, binary classification is used in testing and training because to the unbalanced datasets [22].

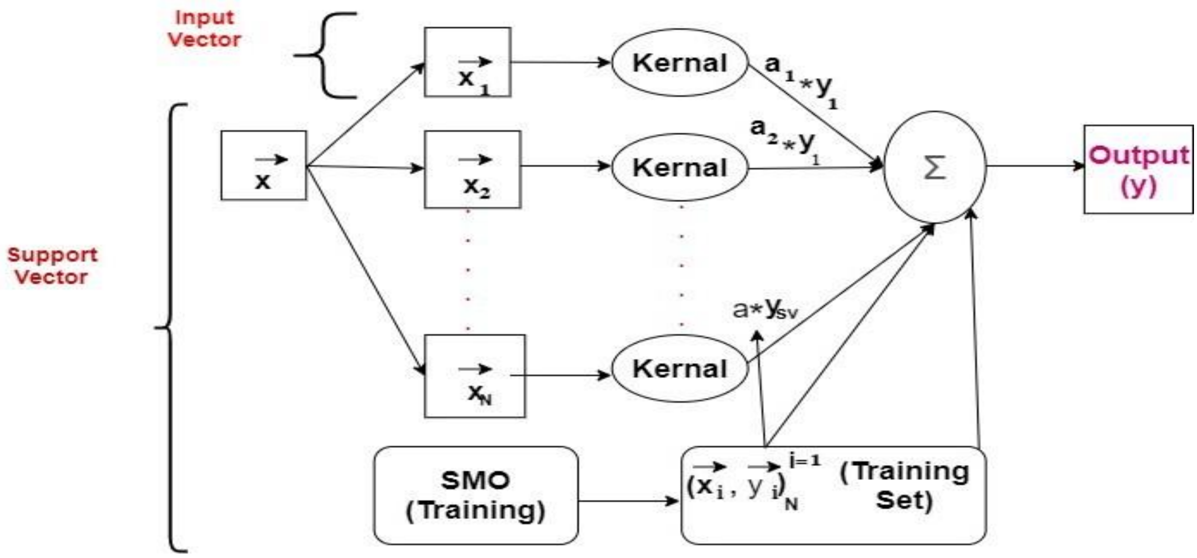

Figure 6. Sequential Minimal Optimization flow diagram

b. Classifier with Random Forests

We use a classifier to improve the accuracy of the results after the pre-classification stage. We used the random forest method, one of the supervised learning algorithms, in our tests. An ensemble-learning method called random forest is used for high-dimensional data categorization [23].

The training step of the RF framework involves the construction of several objective decision trees. Classification with the maximum votes among all decision trees in the entire forest was selected by all decision trees for that class. Random forests' main benefit is that they can compute each feature's score to monitor how that feature is learning based on prediction [24].

$$prediction = \frac{1}{D}\sum_{d=1}^{D} t_d(x') \tag{4}$$

The formula for a tree-based random forest method is shown in Eq. 4, where "x" displays the forecasts for hypothetical samples. In order to forecast feature combinations from a set of provided labels, this summarizes the findings from each individual tree [25]. Bagging, sometimes referred to as bootstrap aggregation, is used to produce an effective classification tree. It has been used on high dimensional data in random forests [26]. Regression trees [22] are then fitted using training data. Additionally, replacement is performed on every sample to ensure uniformity and the highest level of accuracy [27]. Fig. 7 displays a depiction of the classifier.

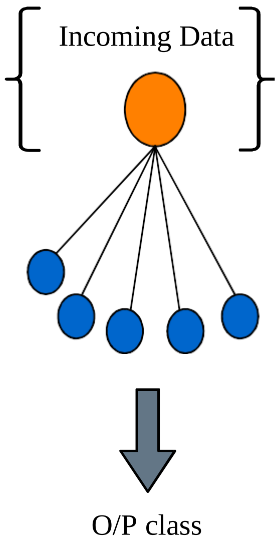

Figure 7. Suggested approach applied over a random forest classifier

4. Results of Experiment and Discussion

In order to assess how well the suggested strategy works, we tested our model using the IMSB dataset and the USC-HAD dataset, respectively. The next sections explore the USC-Human Activities Dataset and IMSB datasets in depth, along with their evaluation outcomes along with comparisons to cutting-edge methodologies.

4.1 Dataset descriptions

The motion data included in the USC-HAD dataset was obtained from a MotionNode device. The MotionNode sensor is referred to as a multi-modal sensor device and includes a 3-axis gyroscope, 3-axis magnetometer, and 3-axis accelerometer. Due to its compact size, this gadget may easily be worn. Extricated data from the gadget is additionally symbolically represented into twelve various actions including forward movement, left movement, right movement, upward movement, downwards movement, diving up, etc. Twelve separate tasks were assigned to a group of 14 individuals (7 men and 7 women), who were using a wearable motion-node device.

Bagging, sometimes referred to as bootstrap aggregation, is used to produce an effective classification tree. It has been used on high dimensional data in random forests. Regression trees are then fitted using training data. Additionally, all samples are replaced to create uniformity and are of 100 Hz, +-6g for the accelerometer, and +-500dps for the gyroscope, respectively. Results for 12 distinct activities are shown in Table I. Our suggested strategy has a considerable mean accuracy of 74.18% due to the least amount of activity overlap.

Motion data from a 3-axis accelerometer is included in the 2nd dataset IMSB. This dataset is further represented by 20 participants (12 men and 8 women) engaging in six sports activities: soccer, hockey, tennis, cricket, volleyball, and golf. More sport-related actions are categorized as dynamic actions in Table II. Our accuracy of 82.63% had a big influence.

Table 1. USC-HAD dataset confusion matrix for 12 various acts

Activity	FM	LM	RM	UM	DM	DU	SIT	STA	SL	UTE	DTE	DF
FM	7	1	1	1	0	1	1	1	1	0	0	0
ML	1	6	1	0	1	0	1	1	1	1	0	0
MR	0	1	7	1	0	0	1	1	1	1	1	0
MU	0	1	0	7	0	0	1	0	0	0	0	0
MD	0	1	0	0	9	0	0	0	1	1	0	0
DU	1	1	1	1	1	8	2	0	0	1	1	0
SIT	0	0	0	0	0	1	7	0	2	1	1	0
STA	0	0	1	1	1	1	1	6	0	1	0	0
SL	0	0	1	1	1	1	1	0	0	7	0	1
UTE	0	1	0	1	1	0	1	0	2	1	6	1
DTE	1	0	0	0	0	0	1	0	0	0	7	0
DF	0	0	0	0	0	0	1	1	0	0	1	8
Mean Recognition=74.18%												

FM stands for forward movement, LM for left movement, RM for right, UM for upward movement, and DM for downwards movement. DU = diving up, SIT = sitting, STA = standing, SL = sleeping, UTE = up the elevator, DTE = down the elevator, and DF = dashing forward.

Sports abbreviations include soccer, hockey, tennis, cricket, volleyball, and golf.

A 64-bit, 8GB RAM, 6th generation Intel Core i5 computer is used for the experiments. For testing and teaching, Google Colab with a Python 3 environment is utilized. On the IMSB dataset, we used the suggested approach with 82.63% accuracy. Table III compares state-of-the-art techniques with the suggested strategy.

Table 2. IMSB Dataset Confusion Matrix of six Sports Activities

Activity	SO	HO	TE	CR	VO	GO
SO	7	1	0	0	0	**0**
HO	1	6	0	0	1	**0**
TE	1	0	6	0	0	**1**
CR	0	0	0	8	0	**0**
VO	1	0	0	1	6	**0**
GO	0	1	1	0	0	**6**
Mean Recognition			**81.25%**			

SO=socker, HO=hockey, TE=tennis, CR=cricket, VO=volleyball, GO=golf

Table 3. Comparison of Advanced methodologies and suggested technique

Approach	Accuracy of IM-Sporting Behaviors (%)
Classification utilizing RF [53]	**73.72**
Classification utilizing LSVM [53]	**78.61**
Suggested technique	**82.63**

5. Conclusion

For speeding up the identification technique in various contexts, we suggested a strong technique in human action recognition for 2 datasets in this study. Preprocessing for the raw signals is included in the system, with a primary emphasis on the feature extraction from 1-D WHT and 1-D LBP increased statistical analysis of data. When used in human activity analysis, these qualities provide reliable findings. Finally, we can say that our suggested model rivals other cutting-edge approaches in terms of accuracy and effectiveness. More features will be added in the future to improve the feature extraction technique.

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