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Efficient Frequency Domain Feature Extraction Model using EPS and LDA for Human Activity Recognition

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Abstract

Activity identification based on machine learning for human computing aims to understand or capture the state of human behavior, its environment, and integrate user by exploiting distinct types of sensors to give adjustment to exogenous computing system. The ascent of universal computing systems requires our environment a solid requirement for novel methodologies of Human Computer Interaction (HCI). Human Activity Recognition (HAR) is playing a vital role in this task. It has an appealing use in health-care system, and monitoring of Daily Living Activities (DLA) of elderly people by offering the input for the development of more interactive and cognitive environments. This paper is presenting a model for recognition of Human Activities. In this proposed model, the Enveloped Power Spectrum (EPS) is used for extracting impulse components of the signal and the Linear Discriminant Analysis (LDA) is used as dimensionality reduction procedure to extract the discriminant features for human daily activity recognition. After completing EPS feature extraction techniques, LDA is performed on those extracted spectra for extracting features using the dimension reduction technique. Finally, the discriminant vocabulary vector is trained by Multiclass Support Vector Machine (MCSVM) to classify human activities. For validating the proposed scheme, UCI-HAR datasets have been used. According to the conducted research, the proposed scheme shows better classification accuracy which has been acknowledged.

Keywords: Human Activity Recognition (HAR); Enveloped Power Spectrum (EPS); Linear Discriminant Analysis (LDA); Multiclass Support Vector Machine (MCSVM).

Introduction

Remote patient monitoring in these days is permitting the crippled and old patients a constant well-being and prosperity supervision while they perform standard exercises for a specific time-period every day. Ongoing populace benchmarks demonstrate that world populace is maturing quickly. For instance, the projection of changes in populace structure by principle age bunches in Europe appear by 2060 the old (individuals more than 65 years) will be close 30% of its populace [1]. This speaks to a disturbing development of over 70% of this age gathering, conveying new difficulties to the examination network, which means to discover suitable choices for guaranteeing sound living to the general population. At present, the elderly people in the USA is nearly 46 million and it will increase to 98 million by the year 2060 which estimates that older population will increase from 15% to 24% by this time. It is anticipated that, this group of people will dramatically increase to the extent of approximately 98 million in amount by the end of 2060 giving rise to 23 percent of the entire population [2].

Human Daily Living Activity Recognition (HDLAR) is an examination field that means recognizing the activities completed by at least one subjects. Accelerometer and other sensors can measure the body movement and generate corresponding movement data. It can be connected for the acknowledgement of human exercises [3]. At the same time, the advancement of smartphone technologies is enabling the cell phone with inertial sensors, for example, accelerometers, gyroscopes, and magnetometers. Initially these sensors were created for improved UIs and gaming alternatives. But as on time passes by, they have now used HAR researches on a large scale as Machine Learning technologies widely available for classification purposes. A few methodologies have been recently proposed in the field of human activities that include assorted application areas, for example, medicinal services, savvy homes, universal processing, encompassing helped living, observation and security [4-7].

AR intends to recognize the activities did by an individual given a lot of perceptions of itself and the encompassing condition. Acknowledgment can be cultivated, for instance, by misusing the data recovered from inertial sensors for example, accelerometers [3]. In modern days, smartphones are incorporated with versatile sensors by default and able to generate a discriminant dataset for different human activities (standing, walking, laying, walking upstairs and downstairs) as different activities have different motions. The advancement of AR applications utilizing cell phones has a few focal points, for example, simple gadget compactness without the requirement for extra fixed hardware, what's more, solace to the client because of the inconspicuous detecting. This diverges from other set up AR approaches which use specific reason equipment gadgets, for example, in [8] or sensor body systems [9]. Although utilization of various sensors might have improved the execution of an acknowledgment calculation, it becomes improbable to anticipate the fact that people will utilize them in their day-to-day activities in the presence of difficulty and the extra time used in wearing them. One downside of this cell phone-based methodology is that vitality and administrations on the cell phone are imparted to different applications and this wind up necessary in gadgets with restricted assets. A novel feature extraction technique was proposed in [10] for HAR, where features were extracted using the Perceptual Linear Prediction (PLP) and Mel Frequency Cepstral Coefficients (MFCCs) where the Hidden Markov Models (HMMs) were used for recognition and segmentation. For human activity segmentation an unsupervised feature extraction model was proposed in [11]. Optimal feature extraction is a tough job in ML. Classification performance depends on extracted features. A useful feature extraction and selection model was proposed in [12], where for classification purpose SVM, ensemble of classifiers, and subspace KNN were used. ML techniques that have been recently utilized for acknowledgment incorporate Gullible Bayes, SVMs, Threshold-based and Markov chains [8]. Specifically, this research makes utilization of SVMs for classification as it was likewise utilized in [13] and [14]. Even though it isn't completely clear which strategy performs better for AR, SVMs have confirmed fruitful application in a few regions including heterogeneous kinds of recognition, for example, written by hand characters [15] and discourse [16].

In machine learning algorithms, fixed-point mathematical standards have been recently contemplated [17, 18] with rating point units that were inaccessible or costly. It has the likelihood of reusing these methodologies for AmI frameworks that need the minimal effort gadgets otherwise it needs permission for load decrease in performing multiple tasks cell phones has these days turn out to be uniquely engaging. In [19] presented the idea of a HF-SVM. The idea of this strategy is to use fixed point number-crunching in the SVM classifier. This feed-forward classifier permits the utilization of this calculation in equipment restricted gadgets. This research has used the same idea and expanded it for multiclass classification. The SVM classifiers were initially introduced for parallel categorization problems yet it extends for versatile plans for multiclass issues for example, in [15]. Specifically, this research has implemented the One-Vs-All (OVA) strategy. The precision is practically identical to remaining identification strategies as shown in [20], and because its scholarly method utilizes meager memory when contrasted for example with the One-Vs-One (OVO) strategy. This is favorable at the point when utilized in restricted assets equipment gadgets. On multichannel time series, deep convolutional neural network was performed for human activity recognition in [21].

However, to extract informative features out of a myriad of digitized sensing signals seems to a tough task. In this regard, this research represents a feature extraction and dimension reduction model based on Human Activity Recognition (HAR). The EPS and LDA are used for feature extraction based on dimensionality reduction of signal spectrum. Finally, multiclass SVM is used with a view to recognize the Human Daily Living Activities (HDLA). In section 2, the proposed method of human daily living activity recognition is presented in detail, whereas in Section 3, the performance of the proposed method is evaluated with different experiments. Finally, Section 4 offers the concluding remarks.

Methodology

This research is targeted for the identification of the Human Daily Living Activity Recognition (HDLAR) grounded on accelerometer and gyro-meter signal. In Figure 1, depicts the working process in a block diagram. The details are described in three subsections correspondingly.

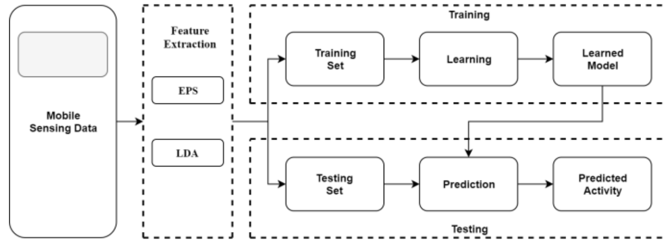

Figure 1. Flow diagram of the proposed scheme.

A. Feature Extraction

Extract feature from signal is essential because of unwanted data into a signal. A plethora of feature extraction techniques is available for signal. In this study, the enveloped power spectrum (EPS) is used for extracting impulse from raw signal data. After performing EPS, Linear Discriminant Analysis (LDA) is performed on those obtained signal spectrums for vocabulary extraction and dimensionality reduction.

a. Enveloped Power Spectrum (EPS)

Imperative use of digital signal processing (DSP) is the enveloped power spectrum (EPS) for estimating the intermittent and irregular signals. The envelope spectrum allows reliable detection of regularities in the periodograms of the time series signal [22]. To investigate machinery signals like accelerometer, gyro-meter i.e., envelope analysis is one of the most powerful techniques for extracting the characteristic frequencies (or defect frequencies) of signal faults. Firstly, enveloped power spectrum's (EPS's) are calculated from original human activity signals using Fast Fourier Transform (FFT) where the periodogram function assesses the power spectrum. This function over an N-point sequence y[n] is characterized by

$$I_N(\omega) = \frac{1}{N}|Y(\omega)|^2$$

where,

$$Y(\omega) = \sum_{n=0}^{N-1} y[n]e^{-jwnT}$$

Y(ω) is the discrete-time Fourier change of y[n].

$$R(n) = \frac{1}{N}\sum_{k=0}^{N-1} y[n+k]\bar{y}[k] \quad for\ |n| \le N-1$$

Or,

$$R(n) = 0 \quad elsewhere$$

It tends to be demonstrated that the converse change of the periodogram is the sample auto relationship function. Figure 2 shown the enveloped power spectrum of each activity signal.

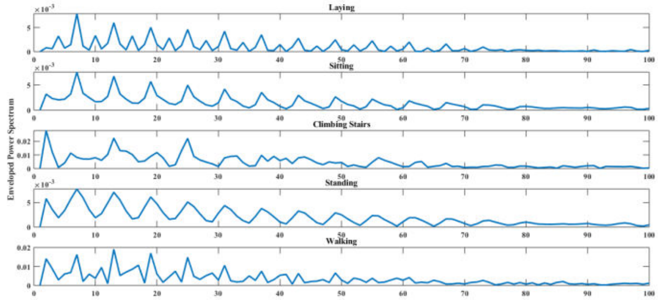

Figure 2. Power spectrum of activity signal.

b. Linear Discriminant Analysis (LDA)

In addition to feature extraction and reduction feature dimension, LDA searches the directions for maximum separation of classes. Fisher's Linear Discriminant Analysis gives the most elevated conceivable separation between various classes of data which causes us to classify the data precisely [23]. To diminish the dimensionality of data utilizing LDA, the inside class covariance matrix was characterized as,

$$S_w = \sum_{k=1}^{k} S_k$$

where,

$$S_k = \sum_{n \in c_k} (x_n - m_k)(x_n - m_k)^T$$

and,

$$m_k = \frac{1}{N_k} \sum_{n \in c_k} x_n$$

and N_k is the number of patterns in class c_k, x_n is the DWT coefficient vector of n^{th} pattern and k is the total number of classes present in the data. Also the between class covariance matrix is defined as,

$$S_B = \sum_{k=1}^{k} N_k (m_k - m)(m_k - m)^T$$

where,

$$m = \frac{1}{N} \sum_{n=1}^{N} x_n = \frac{1}{N} \sum_{k=1}^{K} N_k m_k$$

is the global mean of the data. The total covariance matrix is defined as,

$$S_T = S_B + S_W$$

Finally, the projection matrix is computed as,

$$W = argwmax\{(WS_W W^T)^{-1}(WS_B W^T)\}$$

The LDA coefficients were obtained from the projection matrix as,

$$y = W^T x$$

where x is the DWT coefficient vector in a sub band for a given pattern and y is the vector of LDA coefficients.

B. Classification

At the final stage, human daily living activities are classified by using non-linear Multi-class support vector machine (SVM). Though SVM is a binary classifier it can efficiently classify multi-classes by using a hyper-plane called margin. SVM is widely known for its classification performance which has the potential and capacity for pattern identification for high dimensional data. Although there are some data groups in versatile applications that do not allow to be separated in linear fashion. In other words, no suitable hyperplane exists that can separate the nonlinear datasets into two appropriate categories. In this situation Kernel function can be used to identify the inner meanings of these datasets. The polynomial functions, the hyperbolic tangent and the Gaussian radial basis function can be referred to as examples of nonlinear kernel functions. The technique that is used in this proposed model is the Gaussian radial basis function kernel. This kernel can classify the nonlinear datasets of attributes of activities. The function can be formulated in below:

$$w(ab_i, ab_j) = exp\left(\frac{\|ab_i, ab_j\|^2}{2\gamma^2}\right)$$

Capacity parameter w made from two distinct information namely ab_i, ab_j. The result the equation is computed with the help of free factor namely γ.

Many algorithms are existing for SVM. We have used one-against-all (OAA) SVM is used for human activity classification.

Experiment

A. Dataset

In this study, UCI-HAR dataset is used [24]. UCI-HAR dataset contains in total 10299 numbers of signals with five humans daily living activities (Standing, Sitting, Laying, Walking, Climbing Stairs). Each signal contains 128 samples with three accelerometers (total-acc-x, total-acc-y, total-acc-z) and gyro-meter (body-gyro-x, body-gyro-y, body-gyro-z) data. This dataset is divided into two subsets for training and testing purposes. 50% data are used for training purpose and rest is used for testing purpose. Figure 3 shows the sample activity signal.

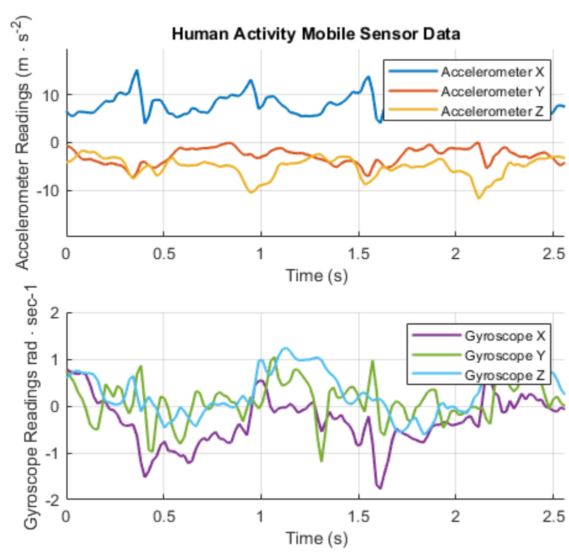

Figure 3. Sample human activity signal.

B. Result Analysis

Proposed model is evaluated by UCI-HAR dataset. This dataset is branched into two subsets. First branched subset contains 50% activity signals for training and another one contains rest of the 50% for testing. EPS is used for signal impulse extraction from sensing activity signal. After applying the EPS, 385 signal spectrums are obtained from 760 samples of a sample activity signal of UCI-HAR dataset. For feature extraction and dimensionality reduction, LDA is performed on extracted signal impulse. After completing feature extraction and dimensionality reduction technique LDA, the feature vector became 123 dimensions for each signal. Then a training feature vector is created for training purpose which is used to train the model. Lastly, the test feature vector that is extracted from the sensing activity signal is used to test the dataset for classification purpose. Table 1 show the class-wise performance of each activity. As shown in Table 2, the model provides better performance from other-state-of-the-art technologies. The overall accuracy of the given model is 98.67% for UCI-HAR dataset.

TABLE 1. CLASS-WISE PERFORMACE (%) OF THE PROPOSED MODEL ON UCI-HAR DATASET.

Activity	**Method**		
	EPS+LDA+MCSVM		
	Sensitivity	Specificity	Accuracy
Standing	100	100	100
Sitting	100	100	100
Laying	100	100	100
Walking	92.69	93.97	93.33
ClimbingStairs	100	100	100

TABLE 2. PERFORMANCE (%) COMPARISION OF THE PROPOSED MODEL WITH OTHER STATE-OF-THE-ART METHODS ON UCI-HAR DATASET.

Authors	**Methods**	**Accuracy**
Yang et al. (2015)	CNN	85.10
Plotz et al. (2011)	DBN	73.20
Zeng et al. (2014)	CNN	76.80
Zhang et al. (2015)	DBN	83.30
Kolosnjaji et al. (2015)	Handcrafted features +Dropout	76.26
Kolosnjaji et al. (2015)	Handcrafted features +Random Forest	77.81
Anguita et al. (2012)	Artificial features + SVM	89.00
Hutchison et al. (2015)	Artificial features + Random Forest	76.26
Li et al. (2014)	Sparse autoencoder + SVM	92.16
Badem et al. (2016)	Stacked autoencoder	97.90
Ignatov et al. (2018)	CNN+Statistical features	97.63
Proposed Method	**EPS+LDA+MCSVM**	**98.67**

Conclusion

This research has presented a vocabulary extraction and reduction approach of dimensionality for Human Activity Recognition (HAR) using sensor signals data. In this feature extraction and feature reduction approach, all features are extracted using EPS and LDA discriminant feature vector for classification purpose. Finally, Multiclass SVM classifier algorithm is utilized for classifying Human Activities. The extent of this research is to employ the present innovation for surrounding technologies, for example, in remote patient observing and smart environments. For validation purpose, experiments have conducted by UCI-HAR dataset. By applying the feature extraction based on EPS and LDA, the described method depicts better classification accuracy which has been acknowledged.

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