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Physical Human Activity Recognition Based on Empirical Model Decomposition Coupled with Classification Models

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Abstract:

Due to the rapid increase in data collected through wearable devices and smartphones, there is a high demand for developing Human Activity Recognition (HAR) techniques. In response, this paper proposes an innovative technique for Human Activity Recognition (HAR). This proposed methodology comprises three key phases: feature extraction, feature selection, and features classification using an ensemble model. First: an Empirical Mode Decomposition (EMD) is applied to decompose the time series data into several modes. Then, a vector of features is extracted from each mode to form the final features vector. The extracted features are sent into several classification models to classify the input time series into different activities. Public datasets are used to evaluate the proposed model. The results demonstrated the ability of the proposed model to classify human activity.

Keywords: HAR, EMD, classification, time series.

1-Introduction Section

Most wearable and mobile applications involve sensor-based human activity recognition (HAR) models. The HAR is considered a hot research area in which sensors data is analyzed using machine learning models [1]. Recently deep learning models based HAR have become in favor of traditional machine learning methods [2–4] . The multi-layered based on deep learning models have improved the recognition rate by extracting features without the need for feature extraction models However, implementing deep learning models on mobile is a challenging task because they require a huge labeled data.

Sensor-based Human Activity Recognition (HAR) methods require a single sensor attached to body [5–7]. Mainly sensors placed in a specific location, such hand, legs and chest. However, experts prefer to use multiple sensors that are distributed on various body locations to enhance accuracy and reliability . Due to the increase in data to be processed, this method requires a longer computational time. To enhance HAR performance by transformation technique-based features extraction model is important to reduce the dimensionality of the data and extract the most useful information .

Many approaches have been designed to identify human activity using several techniques, for example, statistical model, deep learning, transformation technique and symbolic representation-based approach. Zhu et al. [8] applied machine learning models. Martínez-Villaseñor et al. [9] classified human activity using sensory data. Singh et al. [10] designed a model based on Long Short-Term Memory (LSTM). In CNN–RNN was employed for capturing features.

2- Methodology Section

In this section, the main methodology is explained. First: We divide time series data into segments. Then each segment is passed through the EMD model. Second, The resulted modes are analyzed and different features are extracted. Finaly, the extracted features are sent to several classification models.

1- Data Segmentation

The first step involves dividing human activity data into distinct periods or segments. This segmentation is essential because it allows for a more focused analysis of specific activities rather than treating the entire dataset as a single entity. The duration of these segments can vary based on the nature of the activities being analyzed, but they are typically chosen to capture meaningful patterns without losing temporal resolution. For instance, segments might range from a few seconds to several minutes, depending on the complexity and variability of the activities being observed.

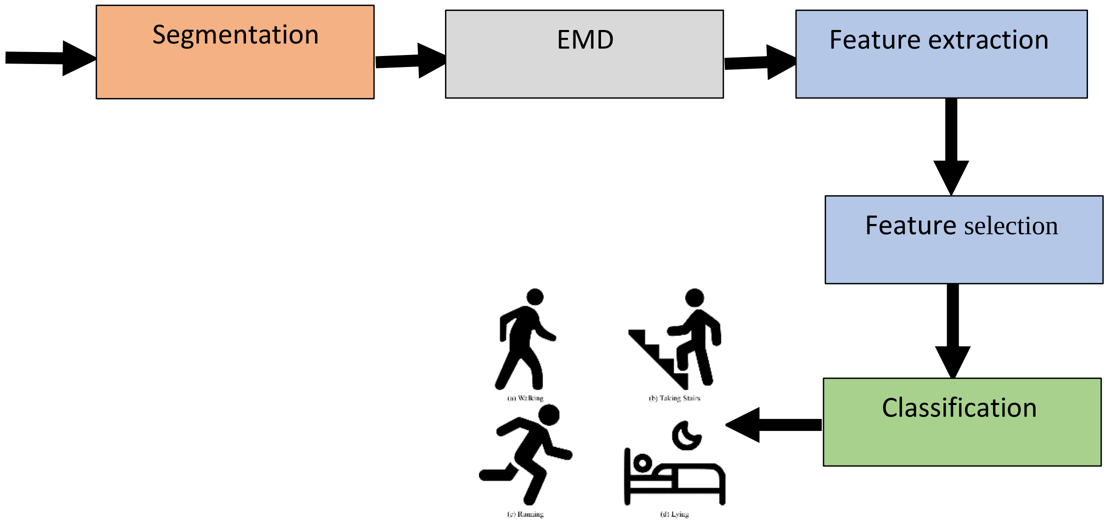

Figure 1.The proposed model for HAR

2.1. Empirical Mode Decomposition:

The empirical mode decomposition (EMD) strategy has been utilized broadly in flag handling. It breaks down input information into a number of oscillatory modes named as inborn mode capacities (IMFs). After that, Hilbert change is connected to each mode to get important recurrence estimations [11]. Nonlinear and nonstationary signals are exceedingly suggested and suited for analyzing EMD, To extricate IMFs, the taking after equation is utilized:

$$S(t) = \sum_{m=1}^{k} imf_{m(t)+r_m(t)} \qquad (1)$$

Where k, is the number of IMFs and $r_m\ (t)$ is the ultimate residue.

The functions of IMFs are those that have the following two characteristics:

1.The absolute variation between the number of zero crossings and the number of function extrema should be less than or equal to one.

2. There is 0 area under the created curve.

The graphic illustrates how to extract IMFS using EMD.2.

Input: human activity data

Output: A set of IMFs

Step1: Discover all the local upper and the local lower values of

nput data.

Step2: Construct R_u (e) and the lower envelop R_l(d) base on cubic spline interpolation;

Step3: Calculate the mean of value: MEan(t) (R_u (t)+ R_l(t))/2;

2.2. Features extraction

We utilized entropy highlights in this paper. Entropy is a measurable metric utilized to measure the sum of chaos in time arrangement information. Much past inquire about has appeared that the entropy highlights had the capacity to analyze information. In this work, we utilized three sorts of entropy highlights named scattering entropy, Inexact entropy, and Shannon entropy

- **Shannon entropy**

Information about human movement is analyzed using Shannon entropy. It is communicated as

$$ShEn = \sum_f p_f \log\left(\frac{1}{p_f}\right) \qquad (2)$$

1. Definition of Variables

p: In this context, p refers to the probability associated with a particular event or outcome. Specifically, p_f denotes the probability of a specific event f occurring within a given set of possible events.

f: This variable represents an individual event or outcome in a discrete probability distribution. The summation runs over all possible events (or outcomes) denoted by f.

- **Approximate entropy**

To calculate the complexity of a time series, estimated entropy is used. It is computed as

$$\mathrm{ApEn}\ (\mathrm{z}, \mathrm{r}, \mathrm{L}) = \rho^{\mathrm{z}}(\mathrm{r}) - \rho^{\mathrm{z}+1}(\mathrm{r}) \qquad (5)$$

Where $\rho^z(\mathrm{r})$ is calculated using the following formula:

$$\rho^z(\mathrm{r}) = \frac{1}{L - z + 1} \sum_i \ln\left(C_i^z(r)\right) \qquad (6)$$

and C_i^z is the correlation integral given by

$$\mathrm{C_i^z}\ (\mathrm{r}) = \frac{1}{\mathrm{L} - \mathrm{z} + 1} \mathrm{L_i^r} \quad \mathrm{i} = 1, 2, \ldots, \mathrm{L} - \mathrm{z} + 1 \qquad (7)$$

- **Dispersion Entropy:**

  Dispersion Entropy is identified the irregularity in time series. To classify human activity, we used dispersion entropy in this research

2.3. Classification models

2.3.1. Support vector machine

SVM is considered to be of great importance and has recently succeeded in obtaining a deal that attracted a lot of attention .The to begin with paper for the SVM was proposed by Vapink; Boser and Guyon. It changes the unique preparing information into a tall measurement by utilizing a nonlinear mapping.

Inside the modern measurement, it looks for the direct ideal isolating hyper plane [12]. In this paper, for factual highlights classification and comparison with the proposed strategy an SVM was utilized as a classifier to recognize the measurable highlights.

2.3.2. K-means algorithm

In insights and machine learning, k-means is considered one of the capable strategies in information classification. It combines straightforwardness and speed which permits us to utilize it on huge databases. Allotments n are calculated from the perceptions in k groups, the perception is the location of one group with the nearest centroid, allotments [13]. It has been broadly utilized to classify information in diverse ranges such computerized picture and biomedical information. In this paper, k-means calculation, had a place to a Measurements and Machine Learning Matlab-Toolbox, was utilized to classify the chart properties and measurable highlights to examine of the viability of utilizing complex organize in rest arrange classification.

2.4 Execution metrics

The assessment of classification comes about plays an imperative part in understanding the quality of an calculation. In this think about, cross approval, affectability, kappa coefficient and perplexity lattice are utilized to assess the exhibitions.

K-cross-validation is utilized to appraise the quality of classification by separating the number of accurately classified comes about by the add up to cases.

- Sensitivity: is a measurable degree which is utilized to assess the execution of a classification tried by measuring the extent of the real positive classification.
- Accuracy: is utilized to calculate the extent of the add up to number of expectations that are adjust.

3.Experimental Results

two datasets were utilized to evaluate the proposed show. reenactments comes about were talked about and displayed in this segment.

3.1Experimental Dataset

Two datasets for human movement acknowledgment were utilized in this paper. The datasets named (WSDM), and PAMAP2. Table 1 showed the points of interest for these datasets.

- PAMAP2 dataset: The dataset was recorded at Division of Expanded Vision German

nvestigate Middle of Fake Insights. A add up to of 9 subjects were included in the recording of the dataset. Each subject performed exercises such as strolling, cycling, running, etc. All subjects were inquired to wear 3 Inertial Estimation Units, and a heart-rate-monitor.

- Thirty-six people provided the WISDM dataset. Each subject performed certain day by day exercises utilizing an Android phone joined to his front leg pockets. An accelerometer sensor was utilized to collect dataset. Each subject performed exercises such as standing, sitting etc .

4- Results Section

The researchers utilized three types of entropy features. Tables 2 and 3 report the results based on the entropy features. From the results, the classification results were improved when all features were combined and used to classify human activity. The SVM scored the highest accuracy rate, while the k-means algorithm obtained the lowest precision. The results showed that the proposed model achieved the highest accuracy when all entropy features were utilized with SVM. Additionally, the proposed model obtained acceptable results with both datasets. The researchers also computed the confusion matrix. Tables 4 and 5 illustrated the results of human activity recognition based on the confusion matrix.

Table 1
In the context of human movement acknowledgment, two significant datasets are utilized: PAMAP2 and WISDM. Below is a detailed table outlining the points of interest for these datasets.

Dataset Name	Recording Location	Number of Subjects	Activities Performed	Sensors Used
PAMAP2	Division of Expanded Vision German Institute	9	Walking, Cycling, Running, etc	3 Inertial Measurement Units, Heart-rate monitor
WISDM	Collected using Android phones in daily settings	36	Standing, Sitting, Walking, etc.	Accelerometer sensor

Table 2
Results of HAR using PAMAP2 dataset

Model	Shannon	Approximate	Despession	All features
SVM	70%	65%	72%	97%
K-means	55%	54%	61%	76%

Table 3
Results of HAR using WISDM dataset

Model	Shannon	Approximate	Despession	All features
SVM	74%	70%	67%	95%
K-means	56%	51%	58%	71%

Table 4
Confusion matric using WISDM

Predict/ground truth	Downstairs	Jogging	Walking	Upstairs	Sitting	Standing
Downstairs	**0.96**	0.00	0.01	0.03	0.00	0.00
Jogging	0.03	**0.096**	0.00	0.00	0.01	0.00
Walking	0.00	0.01	**0.097**	0.01	0.00	0.01
Upstairs	0.01	0.00	0.02	**0.95**	0.02	0.00
Sitting	0.01	0.01	0.01	0.00	**0.97**	0.00
Standing	0.01	0.00	0.00	0.01	0.01	**0.97**

Table 5
confusion matric using PAMAPA2

Predict/ground truth	Downstairs	Laying	Vacuum cleaning	Ironing	Nordic walking	Cycling	Running	Standing	Sitting	Walking	Upstairs
Downstairs	**0.95**	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.03
laying	0.00	**0.97**	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Vacuum cleaning	0.01	0.00	**0.97**	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00
Ironing	0.01	0.00	0.00	**0.96**	0.00	0.00	0.00	0.03	0.00	0.00	0.00
Nordic walking	0.00	0.00	0.00	0.00	**0.96**	0.01	0.00	0.00	0.00	0.03	0.00
Cycling	0.00	0.00	0.00	0.00	0.01	**0.97**	0.01	0.00	0.00	0.01	0.00
Running	0.00	0.00	0.00	0.00	0.02	0.00	**0.96**	0.00	0.1	0.01	0.00
Standing	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.98**	0.01	0.00	0.01
Sitting	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	**0.97**	0.01	0.01
Walking	0.00	0.00	0.00	0.00	0.04	0.00	0.01	0.00	0.00	**0.95**	0.00
Upstairs	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	**0.95**

5- Conclusion Section

The study presented a robust and reliable model for recognizing a variety of human activities.The proposed model showed high accuracy in identifying human activities. The proposed model utilized entropy features to identify and distinguish between human activities. These entropy features proved effective in achieving accurate recognition of human activities. Two different datasets were used to evaluate the performance of the proposed HAR model. Experimental results demonstrated the efficiency and stability of the model when applied to different data sources.

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