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Human Activity Recognition Using Wearable Sensors: Research Review

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Abstract: Research on activity recognition using wearable sensors has made a significant progress and is catching great attention due to its wide range of innumerable applications in different areas such as medical, security and entertainment. The advancement in sensing technologies, nanotechnologies and embedded system has enabled the development of smart activity monitoring systems and surge the use of wearable sensor for daily life physical activity recognition. Despite physical activity recognition being a hot topic for more than a decade, activity recognition is still a challenging task. In this paper we review the studies done so far on human activity recognition based on wearable sensors and discussed various aspects of these researches.

Keywords: Human activity recognition (HAR), activity monitoring, machine learning

Background/ Objectives and Goals

Human activity recognition is a promising research area of artificial intelligence (AI) and has been researched for many years by a lot of researchers. It has attracted people's attention due to its wide range of applications in ambulatory monitoring, fall detection etc. The recent technological advances in the area of sensors and processing units have led to the development of smart wearable devices that are becoming more interesting part of our daily life. Wearable sensors on the basis of their effectiveness and wide area of applications such as, medical, security and entertainment, are getting more and more popular in peoples of all ages. The wearable devices with their high computational power, small size and low cost allow people to interact with these devices as a part of their daily living. These wearable devices can be useful in providing valuable information about people's behavior and thus ensures a modern living environment.

In recent times the usage of wearable sensors has increased particularly in the medical science where there are a lot of different applications for monitoring physiological activities. The unhealthy habits originated by modern lifestyle results in health degradation and lead us suffering from chronic diseases. Wearable health care devices could play a key role to mitigate the health related issues. For example, patient with dementia and other mental pathologies could be monitored to detect abnormal activities and prevent undesirable consequences [1]. Besides this it is possible to monitor heart rate, brain activity, muscle motion, patients body temperature and blood pressure using wearable sensors [2], [3]. Treatment at home is also made possible by the use of wearable sensors for patients after an attack of disease like sleep apnea, Parkinson diseases and so on [4]. With the use of wearable sensors, all the physical activities as well as physiological signals of the patients can be monitored. Falls associated with old age, lack of physical activities and loss of muscles strength, are also a major problem which may lead to several health issues and immediate help needs to be provided to reduce the risk of complications [5]. The recognition of human activity using wearable sensors has also become a task of high interest in the field of military. Soldier's activities along with their locations and health condition could be monitor which is highly beneficial for their performance and safety. Similarly, in the area of sports there is also an increasing trend of various wearable sensors.

Human activity recognition is a very broad and active area of research. Generally human activity recognition can be approached in two different ways, vision-based and sensor-based activity recognition. Vision-based recognition of activities is performed using visual sensing gadget such as video cameras [33]. The data is generated in this approach in the form of digitized visual sequences and then different video processing and computer vision techniques are utilized for feature extraction and pattern recognition. The second category is sensor-based in which the time series data is generated by the sensors which can be used for monitoring activities using different machine learning techniques. A wide range of sensors including accelerometer, gyroscope and motion detectors are available and can be used in two different ways for activity monitoring. Wearable sensors are generally positioned on human body and generate signals when user performs any activity. These wearable sensors can be embedded into clothes, eyeglasses, belts, shoes and mobile devices. A rich content of literature is available for different physical activity recognition like sitting, standing, running, walking and much more complex activities using wearable sensors. For activity recognition using wearable sensors, several different factors are needed to be consider such as the types of sensor, types of activities to be monitor, methodologies for feature extraction, activities classification techniques, computational efficiency and energy consumption.

Activity Recognition

Human activity recognition system consists of mainly five steps: sensing, preprocessing, feature extraction, training and classification. In sensing step physiological data are collected from different sensors at specific sampling rate. Processing step processed the collected data in various ways. For example noise elimination, normalization and segmentation are the most common techniques used in preprocessing. After this the segmented data is used to extract different features utilizing various feature extraction techniques. Training of the classifier is performed based on the extracted features. Here comes the role of machine learning which provides various types of classification algorithms. After classifier's training, the trained classifier is used to classify different activities. The complete data flow for training and classifying different activities is explained in the Fig 1.

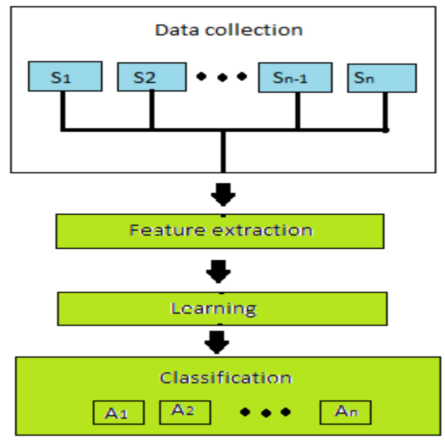

Fig 1: Data flow for activity recognition system

Wearable activity recognition system comprises of body worn sensors tightly coupled with human body acquire data from these sensors in accordance with activity. This bunch of data is processed to classify different activities using machine learning algorithms. A complete description of each step involve in activity recognition is given in the remaining sections.

Feature Extraction and Selection

Feature extraction and selection is considered as the working horse of machine learning and is one of the key steps for accurate classification of activities. The main purpose of the feature selection step is to select the minimum subset of most suitable and most relevant features. The proper extraction and selection of feature significantly increase the accuracy of classification and improves computational performance. Generally two approaches are used for feature extraction from time series data: structural and statistical [6]. Statistical methods such as 'Fourier transform' or 'Wavelet transform' use quantitative characteristics of the data to extract features, while structural approach consider the interrelation among data for feature extraction. Table I gives a summary of feature extraction methods. For activity recognition, time window based approach is followed for signal segmentation. All features are extracted using time window whose length has a high impact on accuracy of activity recognition [34]. More the window length betters the significant information it contain. On the other hand short time window cannot provide sufficient information to sufficiently describe the performed activity; however, using short time window enhances the feature extraction performance. Different window length have been used in literature such as 1s [7], 1.2s [8], 3s [9], 5s [10], 7s [11], 12s [12] and so on up to 30s.

Table 1: Summary of feature extraction method

Group	Methods
Time domain	Mean, standard deviation, variance, interquartile range (IQR), mean absolute deviation (MAD), correlation between axes, entropy, and kurtosis [13], [14]–[16], [17], [18], [19].
Frequency domain	Fourier Transform (FT) [17], [18] and Discrete Cosine Transform (DCT) [10].
others	Principal Component Analysis (PCA) [20], [10], Linear Discriminant Analysis (LDA) [18],

After feature extraction, most appropriate set of feature is selected using feature selection techniques. Several feature selection techniques has been presented in the literature. For instance the proposed feature selection method by Zhang et al. [22] organizes the extracted features from the time series data in multiple subsets in a multilayer rather than utilizing all selected features as one set. An efficient feature selection via analysis of relevance and redundancy is presented in the literature [23] which can efficiently eliminate redundant features via explicitly handling feature redundancy. Clustering, filters and wrapper based feature selection methods are also presented in the literature [24], [25].

Classification

Human activity recognition uses different machine learning techniques to build patterns to analyze and predict data. These techniques discover patterns from a set of observations or instances also called training set. Each instance is a representation of a feature vector extracted from signals within a time window. All these approaches are categorized into two supervised techniques which deal with labeled data and unsupervised techniques which deal with unlabeled data. Supervised learning is a very productive field and a large numbers of efficient and well known algorithms come under this category. The description of these algorithms is as follows. Decision tree is one of the famous classifier of this category in which attributes are mapped to nodes and edges represent the possible attribute values. The most widely used decision tree algorithm is C4.5 in which the attribute to be placed in the top nodes are selected based on information gain. Support vector machine is another classifier broadly used in activity recognition. Bayesian method which calculates posterior probabilities for each class using estimated conditional probabilities from the training set is also one of the most widely used machine learning techniques. Besides these techniques, instance based learning approaches and neural networks are also used for the classification of different activity. A survey of the most important classifier used in human activity recognition using wearable sensors is given in table 2.

Table 2: Summary of Classification algorithms

Types	Classier	References
Decision tree	C4.5 and ID3	[26], [16], [17], [19]
Domain transform	Support Vector Machines	[20], [27]
Fuzzy Logic	Fuzzy Basis Function	[18], [15], [28]
Bayesian	Naive Bayes and Bayesian Networks	[26], [14], [17], [29]

Conclusion

In this paper, we reviewed the work done so far on human activity recognition using wearable sensors. We consider studies related to key steps of activity recognition such as feature extraction, feature selection and classification. The fundamentals of feature extraction, feature selection and machine learning are also included. It is expected that in future many more comfortable and high-performance wearable devices will be available with activity recognition for different applications in smart home and health care.

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