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A Review on Human Activity Recognition using Deep Learning

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Abstract

In the past decades, Human Activity Recognition (HAR) grabbed considerable research attentions from a wide range of pattern recognition and human–computer interaction researchers due to its prominent applications such as smart home health care. The wealth of information requires efficient classification and analysis methods. Deep learning represents a promising technique for large-scale data analytics. There are various ways of using different sensors for human activity recognition in a smartly controlled environment. Among them, physical human activity recognition through wearable sensors provides valuable information about an individual's degree of functional ability and lifestyle. There is abundant research that works upon real time processing and causes more power consumption of mobile devices. Mobile phones are resource-limited devices. It is a thought-provoking task to implement and evaluate different recognition systems on mobile devices. This work present the review of literature for the recognition of human activity using wearable sensor.

Keywords: *Human Activity, Deep Learning, Pattern Recognition, Mobile devices.*

1. Introduction

Human Activity Recognition (HAR) aims to identify the actions carried out given a set of observations of a person and his/her surrounding environment. Recognition can be accomplished by exploiting the information retrieved from various sources such as environmental or body-worn sensors [1]. Some approaches [2], [3] have adapted dedicated motion sensors to fit different human body parts such as waist, wrist, chest and thighs. They have achieved great classification performance. However, these sensors usually make a common user not that comfortable and do not provide a long-term solution for activity monitoring, due to such issues, as sensor repositioning after dressing. HAR has become an attractive research field due to its importance as well as many challenges brought to the research community. Researchers use these HAR systems as a medium to get information about people's behaviors. The information is commonly collected from the signals of sensors such as ambient and wearable sensors. The data from the signals are then processed through machine learning algorithms and recognize the events. Hence, such HAR systems can be applied in plenty of useful and practical applications in smart environments such as smart home health-care systems. For example, a smart HAR system can continuously observe patients for health diagnosis and medication. In addition, it can be applied for automated surveillance of public places to predict crimes that may occur in the near future.

1.1 Wearable Sensor

Since the appearance of the first commercial hand-held mobile phones in 1979, it has been observed an accelerated growth in the mobile phone market. Mobile devices have almost become easily accessible to virtually everybody now. Smartphones, which are a new generation of mobile phones, are now offering many other features such as multitasking and the deployment of a variety of sensors, in addition to the basic telephony. Current efforts attempt to incorporate all these features while maintaining similar battery lifespans and device dimensions. The integration of these mobile devices in our daily life is rapidly growing. It is envisioned that such devices can seamlessly keep track of our activities, learn from them, and subsequently help us to make better decisions regarding our future actions.

Smartphones have been bringing up new research opportunities for human centered applications where the user is a rich source of context information and the phone is the first hand sensing tool. Latest devices come with embedded built-in sensors such as microphones, dual cameras, accelerometers, gyroscopes, etc. The use of smartphones with inertial sensors is an alternative solution for HAR. These mass marketed devices provide a flexible, affordable and self-contained solution to automatically and unobtrusively monitor Activities of Daily Living (ADL) while also providing telephony services. Consequently, in the last few years, some works aiming to understand human behavior using smartphones have been proposed. For instance, one of the first approaches has been exploited an Android smartphone for HAR employing its embedded triaxial accelerometers. Improvements are still expected in topics such as in multi-sensor fusion for better HAR classification, standardizing performance evaluation metrics, and providing public data for evaluation.

Currently, smartphones, wearable devices, and internet-of-things (IoT) are becoming more affordable and ubiquitous. Many commercial products, such as the Apple Watch, Fitbit, and Microsoft Band, and smartphone apps including Runkeeper and Strava, are already available for continuous collection of physiological data. These products typically contain sensors that enable them to sense the environment, have modest computing resources for data processing and transfer, and can be placed in a pocket or purse, worn on the body, or installed at home [4]. Accurate and meaningful interpretation of the recorded physiological data from these devices can be applied potentially to HAR. However, most current commercial products only provide relatively simple metrics, such as step count or cadence. The emergence of deep learning methodologies that extract different discriminating features from the data, and increased processing capabilities in wearable technologies. The ability of simultaneous activity classification and the decreasing size of computing platforms give rise to the possibility of performing detailed data analysis in situ and in real time. Today's handheld PCs are often more powerful than desktop computers of the 1990s. Once a rare commodity, computers are now embedded in everything - toys, cars, cell phones, and even bread makers.

In the case of wearable sensors in activity recognition, a smartphone is an alternative to them due to the support of the diversity of sensors in it. Handling sensors such as accelerometers and gyroscopes along with the device with wireless communication capabilities made smartphones a very useful tool for activity monitoring in smart homes. Besides, smartphones are very ubiquitous and require almost no static infrastructure to operate it. This advantage makes it more practically applicable than other ambient multi-modal sensors in smart homes. As recent smart phones consist of inertial sensors (e.g., gyroscopes and accelerometers), they can be appropriate sensing resources to obtain human motion information for HAR. HAR has been actively explored based on a distinguished kind of ambient and wearable sensors. Some instances of such sensors include motion, proximity, microphone, and video sensors. Most of the ambient sensor-based latest HAR researchers have mainly focused on video cameras as cameras make it easy to retrieve the images of surrounding environment. Video sensors are included with some other prominent sensors in some work related to novel ubiquitous applications. Though video sensors have been very popular for basic activity recognition. They face very many difficulties for ordinary people to accept due to a privacy issue . On the contrary, wearable sensors such as inertial sensors can overcome this kind of privacy issues and hence, deserve more focus for activity recognition in smart homes.

In the past years, many HAR systems used accelerometers to recognize a big range of daily activities such as standing, walking, sitting, running, and lying. For instance, some researchers have already explored the accelerometer data to find out the repeating activities such as grinding, filling, drilling, and sanding [5] [8]. The others, have performed elderly peoples' fall detection and prevention in smart environments [9]. Majority of the afore mentioned systems adopted many accelerometers fixed in different places of a human body. However, this approach apparently not applicable to daily life to observe long-term activities due to attachment of many sensors in the human body and cable connections. Some studies [6] [8] tried to explore the data of single accelerometers at sternum or waist. These studies have reported substantial recognition results of basic daily activities such as running, walking, and lying. However, they could not show good accuracy for some complex activity situations such as transitional activities, e.g., sit to stand, lie to stand, and stand to sit.

1.2 Deep Learning

Deep-learning is such an approach that helps the system to understand the complex perception tasks with the maximum accuracy. Deep learning is also known as deep structured learning and hierarchical learning that consists of multiple layers which includes nonlinear processing units for the purpose of conversion and feature extraction. Every subsequent layer takes the results from the previous layer as the input.

The learning process takes place in either supervised or unsupervised way by using distinctive stages of abstraction and manifold levels of representations. Deep learning or the deep neural network uses the fundamental computational unit, i.e. the neuron that takes multiple signals as input. It integrates these signals linearly with the weight and transfers the combined signals over the nonlinear tasks to produce outputs.

In the "deep learning" methodology, the term "deep" enumerates the concept of numerous layers through which the data is transformed. These systems consist of very special credit assignment path (CAP) depth which means the steps of conversions from input to output and represents the impulsive connection between the input layer and the output layer. It must be noted that there is a difference between deep learning and representational learning.

Representational learning includes the set of methods that helps the machine to take the raw data as input and determines the representations for the detection and classification purpose. Deep learning techniques are purely such kind of learning methods that have multiple levels of representation and at more abstract level. Figure 1 depicts the differences between the machine learning and deep learning.

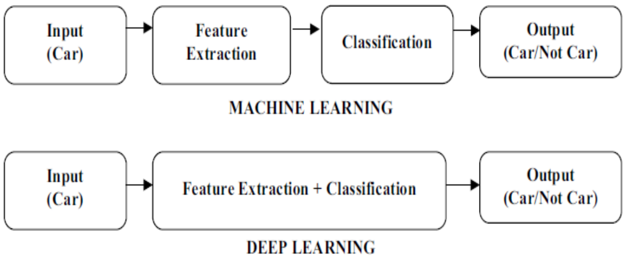

Fig. 1: Difference between machine learning and deep learning

Deep learning techniques use nonlinear transformations and model abstractions at a high level in large databases. It also describes that a machine transforms its internal attributes, which are required to enumerate the descriptions in each layer, by accepting the abstractions and representations from the previous layer. This novel learning approach is widely used in the fields of adaptive testing, big data, cancer detection, data flow, document analysis and recognition, health care, object detection, speech recognition, image classification, pedestrian detection, natural language processing and voice activity detection. Deep learning paradigm uses a massive ground truth designated data to find the unique features, combinations of features and then constructs an integrated feature extraction and classification model to figure out a variety of applications. The meaningful characteristic of deep learning is the data that uses general-purpose methods, various extensive features and no intervention of human engineers. Facebook has also created Deep Text for the classification of the massive amount of data and cleaning the spam messages.

2. Related Work

Igor Khokhlov et al., (2020) investigated and analyze sensor mounting position, sensor types, and data type influence on activity recognition accuracy. Also, we render and analyze the benefits of using a RNN classifier over a more static classifier such as J48 and Naive Bayes algorithms in our empirical study. Dynamic classifiers such as RNN are far superior to rather static classifiers such as J48, Naive Bayes, and Random Forest algorithms when it comes to classification accuracy for recognizing the activity. These observations can be bolstered for all cases of experiment viz. using data from the accelerometer to train our classifier, using data from both accelerometer and gyroscope to train our data and finally, analyzing individual gait of users. Static classifiers benefit significantly from using data points from multiple sensors viz. accelerometer and gyroscope when it comes to classification accuracy for activities. We noticed a 15-20% increase in classification accuracy when readings from the gyroscope we used to supplement the readings from the accelerometer for recognizing activities.

Sakorn et al., (2020) proposed a novel framework for multi-class wearable user identification, with a basis in the recognition of human behavior through the use of deep learning models. The results for the two basic models, namely, the Convolutional Neural Network (CNN) and the Long Short-Term Memory (LSTM) deep learning, showed that the highest accuracy for all users was 91.77% and 92.43%, respectively. With regard to the biometric user identification, these are both acceptable levels. The ensemble method that is proposed was developed using experiments involving four specific deep learning models, selected to enhance user identification efficiency.

Henry Friday, et al., (2018) provide the best comparison and categorisations of recent events in the research community, we reviewed the training and optimisation strategies adopted by different studies recently proposed for mobile and wearable based human activity recognition. Furthermore, classification and performance metrics with different validation techniques are important to ensure generalisation across datasets. These approaches are adopted to avoid overfitting the model on the training set. Also, we provide some of the publicly available benchmark datasets for modelling and testing deep learning algorithms for human activity recognition. Some of these datasets that are widely used for evaluation are OPPORTUNITY, Skoda, and PAMAP2 which are also popular with classical machine learning algorithms.

Reza Akhavian and Amir H. Behzadan, (2018) machine learning-based framework is designed and implemented to extract durations of activities performed by construction workers from wearable sensors. This framework uses accelerometer and gyroscope sensors embedded in smartphones that are worn by field workers. Data analysis and processing is applied to the collected data to train machine learning algorithms capable of detecting and classifying construction workers' activities. Once the activities are identified, their durations are calculated using the time stamps of the collected data. Results indicate that smartphones can be used as cost-effective, ubiquitous, and computationally powerful means of enabling data-driven DES models with enhanced reliability over traditional simulation models.

Daniele Rav et al., (2017) propose a deep learning methodology, which combines features learned from inertial sensor data together with complementary information from a set of shallow features to enable accurate and real-time activity classification. The design of this combined method aims to overcome some of the limitations present in a typical deep learning framework

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where on-node computation is required. To optimize the proposed method for real-time on-node computation, spectral domain preprocessing is used before the data are passed onto the deep learning framework. The classification accuracy of our proposed deep learning approach is evaluated against state-of-the-art methods using both laboratory and real world activity datasets. Our results show the validity of the approach on different human activity datasets, outperforming other methods, including the two methods used within our combined pipeline.

Victor Bergelin, (2017) examined the viability of detecting and further on predicting human behavior and complex tasks. The field of smoking detection was challenged by using the Q-sensor by Affective as a prototype. Further more, this study implemented a framework for future research on the basis for developing a low cost, connected, device with Thayer Engineering School at Dartmouth College. With 3 days of data from 10 subjects smoking sessions, events were detected with just under 90% accuracy using the Conditional Random Field algorithm. However, predicting smoking with Electrodermal Momentary Assessment (EMA) remains an unanswered question.

Min-Cheo and Sunwoong Choi (2018) propose a human activity recognition system that collects data from an off-the-shelf smartwatch and uses an artificial neural network for classification. The proposed system is further enhanced using location information. We consider 11 activities, including both simple and daily activities. Experimental results show that various activities can be classified with an accuracy of 95%.

Abdulhamit Subasi, et al., (2018) Adaboost ensemble classifier is used to recognize human activity data taken from body sensors. Ensemble classifiers achieve better performance by using a weighted combination of several classifier models. Many researchers have shown the efficiencies of ensemble classifiers in different real-world problems. Experimental results have shown the feasibility of Adaboost ensemble classifiers by achieving the better performance for automated human activity recognition by using human body sensors. Results have shown that ensemble classifiers based on Adaboost algorithm significantly improve the performance automated human activity recognition (HAR).

Problem Statement

In the last few decades, many HAR systems were developed. Researchers have focused on several activities in distinguished application domains. For instance, the activities can include walking, running, cooking, exercising, etc. In terms of their duration and complexity, these activities can be categorized into three key groups: short, simple, and complex activities. The first group consists of activities with very short duration such as transition from *sit to stand*. The second group refers to basic activities like walking and reading. The last group basically include the combinations of progressions of basic activities with the interaction with other objects and individuals. Such kind of activities can be partying or official meeting together.

Some studies have introduced the concept of a Hardware-Friendly SVM (HFSVM). It exploits fixed point arithmetic in the feed-forward phase of an SVM classifier, so as to allow the use of this algorithm in hardware-limited devices. The SVM algorithm is originally proposed only for binary classification problems but it has been adapted by using different schemes for multiclass problems. In particular, the One-Vs-All (OVA) method is as its accuracy is comparable to other classification methods as demonstrated, and because its learned model uses less memory when compared to an One-Vs-One (OVO) method. This is advantageous when used in resource-limited hardware devices. Utilizing wearable sensors, numerous works has been done in the literature with various classification algorithms for recognizing human activity. Most of the algorithms include SVM-based classification, neural network-based one and pattern mating based one. For instance, a neural system classifier for line activity recognition is proposed. However, actualizing such a complicated method in a wearable sensor system is restricted by the calculability of the implanted framework. Other more methodical ways to deal with classifying activities based on decision tree classifier. However, it has low recognition accuracy rate at 70%. Therefore, to achieve high accuracy with low computation cost is a key challenge of human activity recognition.

3. Conclusion

The idea of this work is to present the literature work done using a deep learning model to solve the Human Activity Recognition (HAR) problems. This works surveys the state-of-the-art work in human activity recognition based on wearable sensors. HAR systems are introduced according to their response time and learning scheme. Meanwhile, several systems are also qualitatively compared in terms of response time, learning approach, obtrusiveness, flexibility, recognition accuracy, and other important design issues. The fundamentals of feature extraction and machine learning are also included, as they are important components of every HAR system. The already presented approach is complex and lengthy in implementation. So in future work, need to develop such approach which would be easy and takes less computation time which will help to improve the accuracy.

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