Wearable Sensor Data for Human Activity Recognition Based on DRNNs

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Abstract:

Wearable sensors provide a user friendly and non-intrusive mechanism to extract user related data that paves the way to the development of personalized applications. Within those applications, Human Activity Recognition (HAR) plays an important role in the characterization of the user context. Outlier detection methods focus on finding anomalous data samples that are likely to have been generated by a different mechanism. This paper combines outlier detection and HAR by introducing a novel algorithm that is able both to detect information from secondary activities inside a main activity and to extract data segments of a particular sub-activity from a different activity. Several machine learning algorithms have been previously used in the area of HAR based on the analysis of the time sequences generated by wearable sensors. Deep Recurrent Neural Networks (DRNNs) have proven to be optimally adapted to the sequential characteristics of wearable sensor data in previous studies. A DRNN based algorithm is proposed in this paper for outlier detection in HAR. The results are validated both for intra and inter-subject cases and both for outlier detection and sub-activity recognition using 2 different datasets.

Keywords

Human Activity Recognition, Wearable Sensors, Outlier detection, Machine Learning, Deep Learning, Recurrent Neural Networks, LSTMs

INTRODUCTION

Human Activity Recognition (HAR) is a research area which focuses on automatically detecting/assessing what a particular human user is doing based on related sensor data. Recognizing what the user is doing provides valuable contextual information to help user-centered applications to better adapt to the user needs in many different areas. In fact, HAR has been successfully applied to several areas such as sport training, remote health monitoring, health self-management, military applications, gaming, home behavior analysis, gait analysis and gesture recognition Based on the granularity of the activity being recognized, activities could be broken into movements or gestures or grouped together into sequences of activities (complex or composed activities). Based on the type of sensor used, the activities could be recognized using wearable sensors, sensors attached to objects which are handled by the user or sensors in the environment (such as cameras and Bluetooth beacons). Different machine learning based algorithms have been used over the past decades to solve the human activity recognition problem These algorithms are trained (either in a supervised or semi-supervised way) with labeled data assigning raw sensor data fragments to a particular activity (class). Several datasets are publically available (such as those found in) with labeled sensor data which have been commonly used in previous research studies. These datasets assign labels to data which may have information from secondary activities (either executed in a sequential or overlapping way). Training the machine learning based classification algorithms including these secondary-activity sensor data introduces training errors which have an impact in the performance of the recognition phase (when assigning a class or activity to a new no labeled segment of data). In this paper, a novel technique for detecting anomalous segments in the raw temporal sequences of sensor data is presented (fragments of data in the temporal sequence recorded while performing a particular activity which deviate so much from other fragments as to arouse suspicions that they were generated by the execution of a different activity). These anomalous sections (or outliers) could be removed from the training data to better train the machine learning algorithms as well as for outlier detection. Section IV presents the proposed architecture for outlier detection in wearable sensor data for Human Activity Recognition (HAR) based on the use of Deep Recurrent Neural Networks (DRNN) using Long Short Term Memory (LSTM) cells. Section V is dedicated to the description of the datasets used for validation. Results are presented

DEEP LEARNING METHODS

generic formulation for the Human Activity Recognition (HAR) problem, as well as a survey of former methods to solve it was captured in The general dataflow for HAR comprises several common steps including the activity related data acquisition from sensors when performing the activity, the extraction of relevant features describing the sensed information and the use of a learning method which is trained based on known labeled data and applied to new unknown data for activity recognition A similar survey on former HAR research studies defined the typical activity recognition chain as a set of the following tasks: raw data acquisition, preprocessing, segmentation, feature extraction and classification. The way in which the features are defined and selected plays a very important role in the final performance of the system. Former studies used two major approaches to extract features from time series data: statistical and structural. Both of them are hand-crafted methods which transform the raw sensed data into particular pre-defined characteristics or descriptors. Hand-made features were formerly used with shallow learning algorithms for classification of activities . Shallow structures could be defined by the low depth of the paths of intermediate trainable units between the input and the output layers . These trainable intermediate units are trained to learn the relationship between the input features and the output class. When the depth of the path grows the machine learning methods turn to Deep Learning architectures. In recent years, deep learning methods have been more and more used for HAR, which achieves unparalleled performance in many areas such as visual object recognition, natural language processing, and logic reasoning . Deep learning can largely relieve the effort

OUTLIER DETECTION BASED ON DEEP LEARNING

Hawkins provided a definition of an outlier as 'an observation which deviates so much from other observations as to arouse suspicions that it was generated by a different mechanism'. Several methods have been proposed since then in order assess those deviations. The authors in provided a categorization of anomaly detection algorithms and methods including the following categories: statistical methods, distance-based methods, density-based methods, clustering techniques and adaptations of machine learning algorithms for classification problems to novelty detection (methods such as Neural Networks, and One-class Support Vector Machines). The authors in provided a deeper study of some of the data mining techniques that could be used to detect the surprising behavior hidden within data such as clustering methods and classifiers. A similar paper in also concluded that anomaly detection has been widely studied by using adaptations of machine learning techniques, where it is also known as outlier detection, deviation detection, novelty detection, and exception mining.

The development of deep learning algorithms and techniques has also been applied for outlier detection in recent years. The authors in made use of several stacked auto encoders and a single class SVM to detect anomalies in images. By stacking together several auto encoders, the architecture focuses on automatically learning hierarchical features in an unsupervised way. A similar idea based on Deep Structured Energy Based Models (DSEBMs) is presented in The authors also solve the anomaly detection problem based on the direct modeling of the data distribution with deep learning architectures. The authors state that using Energy Based Models (EBMs) naturally corresponds to identifying data points that are assigned low probability values by the model. Using a trained DSEBM, the samples that are assigned a probability value bellow a pre-chosen threshold will be marked as outliers. The authors in [used a similar method based on demising autoencoders to detect outliers. Previously proposed methods in for outlier detection based on deep learning architectures do not consider the sequential nature of the time series generated by wearable sensors. In a similar way that Deep Recurrent Neural Networks (DRNNs) have outperformed other deep learning architectures for Human Activity Recognition (HAR) as described in the previous section, it is likely that they also perform well for outlier detection in wearable sensor data. This paper proposes and analyses a novel architecture for outlier detection in a HAR using a DRNN based on LSTM cells.

PROPOSED ARCHITECTURE

The proposed architecture is captured in Figure 1. The circles in the lower part of the image represent the recent values of the input signal. In our case, the input signal will be based on the data samples obtained from a sensor in a wearable device although the algorithm could be applied to other types of sequential data as well. Depending on the type of sensor and the way in which the device is attached to the body, a preprocessing phase would be convenient in order to improve the quality of the raw data. In the case of using tri-axial accelerometers (as used in the validation part of this paper), using data from sensors from different datasets using different sampling frequencies, a resampling mechanism should be executed in order to generate data sequences at a predefined rate. The resampling process will also be used to regenerate missing values in the sequence by interpolating the information from the closest data points. Moreover, the acceleration values in the device coordinate system do not provide an optimal representation of the data since the device orientation could vary from user to user, from a data recording from a single user to a different recording for the same user and even for intra-recording samples if the device is not attached completely tight to the body. A better representation of the input acceleration signal is obtained by projecting the raw acceleration values to a geo-referenced coordinate system. Further preprocessing in order to filter noise has not been used in this paper. The input samples in Figure 1 are fed into a Recurrent Neural Network (RNN). Stacking together several layers, a deep representation will be created. A deeper representation will be able to better adjust to finer details in the data but will also require more samples and more time to train and is prone to show over fitting and generalization issues. In the particular case of the authors found out that increasing the depth of the RNN architecture achieved a better performance only for a three-layer architecture. In the proposed architecture in Figure 1, the output of the DRNN part will be connected to a dense connected layer which will be trained to minimize the mean square error with the upcoming samples in the input sequence. Once the architecture in Figure 1 is trained with data segments for a particular activity, outliers will be detected by applying the trained network to each data segment and comparing the similarity of the reconstructed (predicted) output with the real upcoming values in the sequence. Different correlation coefficients could be the intra-subject intra-dataset validation is expected to show better results since some peculiar characteristics of some users are not included in the data from the rest of participants. Inter-subject inter-dataset will use all the participants in the dataset in to train the architecture in Figure 1 and the participants in the dataset in for validation.

INTRA-SUBJECT OUTLIERDETECTION

Intra-subject outlier detection is based on using the acceleration data from each user to detect outliers for that particular user. The architecture proposed in section IV, when trained with the data of a particular user for a particular activity, will learn the characteristic patterns in the data in order to minimize the error when predicting the upcoming segment of data for that particular participant. If the trained architecture is presented with a segment of acceleration data from a different activity, the expected quality of the predicted sequence will decrease. In that way, comparing the Pearson correlation coefficient between the predicted data and the real data for the upcoming data segment will provide a mechanism to estimate whether the current data belongs to the activity used to train the algorithm or to a different one. As in previous outlier detection algorithms, the dataset used in the training phase should optimally be outlier-free, containing only data for the particular activity to be modeled. In the particular case of the dataset used in the validation experiment in this paper the data labeled as belonging to each activity contained several segments corresponding to different activities. In order to cleanse the data from potential outlier segments, the algorithm proposed in section IV can be executed in 2 iterations. A first iteration is executed in order to remove the segments which show a lower reconstructed similarity as compared to the majority of the segments in the dataset. A percentage value could be used for selecting the most similar data segments. In our case, the Pearson correlation coefficient in the reconstruction below a similarity threshold has been used (setting the threshold in r=0.8 for the results presented in this section; other values such as r=0.7 and r=0.9 have provided similar results). Once the estimated outlier segments have been removed, a second iteration with the remaining data is executed in order to train the architecture in section IV for a particular activity. In order to validate the intra-subject outlier detection results, the walking activity for each participant has been selected. The dataset in uses several accelerometers attached to different parts of the body in the recording of the data. The turning around, being stopped, and significantly slowing down the pace without fully stopping. A threshold for the Pearson correlation coefficient of 0.3 has been used. Table III captures the same results for the case in which pre-estimated outliers are removed first The 11 segments were detected as outliers after the removal of pre-detected outliers (2 iterations). Table IV shows that the similarity threshold has to be raised to 0.5 in order to be able to detect the 11 turnaround segments in the case of no outlier pre-filtering. Raising the similarity threshold will increase the number of false

DETECTION OF PARTICULAR SUB-ACTIVITIES

Once the architecture in section IV has been trained to recognize a particular activity for a particular user, the trained algorithm could be used to try to recognize segments of that activity inside a wider execution of a different activity. In this section, the results for detecting walking segments when running, climbing down and climbing up stairs for the case of intra-user training are captured. From the 15 users in the dataset, user 4 has been selected for 2 main reasons: the running data contains 4 walking segments inside and the user is one of the few that performs the climbing up and down activities using an indoors staircase with 24 flat segments connecting stair fragments. Figure 13 shows the results for the execution of the algorithm proposed in section IV, trained with the walking data for participant 4, to detect similarities in the running activity recording. The 60-sample windows (1.2 seconds) predicted with a similarity higher than 0.9 (as measured by the Pearson correlation coefficient) are shown in blue. The ground truth consisting of the regions visually assessed in the video information in the dataset containing walking data segments is shown in red.

CONCLUSIONS

A novel architecture based on the use of Deep Recurrent Neural Networks (DRNN) in Human Activity Recognition (HAR) able to both detect the presence of anomalous segments of data inside the execution of a main activity and detect regions of a particular secondary activity inside a main activity has been presented and validated in three different scenarios: Intra-dataset, intra-subject validation: using the data for a single user for training and validation. Intra-dataset, inter-subject validation: using the data of all the users in a single dataset except one for training and the data for the left-aside user for validation. Inter-dataset, inter-subject validation: using the data for all the users in a dataset for training and the users in the second dataset for validation. One of the major applications of outlier detection methods is to perform a data pre-processing cleansing task. In fact, the proposed algorithm for outlier detection shows better results if executed in 2 iterations: a first one to cleanse the dataset in order to remove secondary activity related data and a second one to optimally train the algorithm with single activity information and optimal outlier final detection. In order to validate the results for the outlier detection approach, 3 major outlier types have been identified in the dataset in and the algorithm has been configured with different thresholds to assess the results. For outlier types generating acceleration information significantly different from the one in the main activity (such as very slow walking, or being completely stopped), all the configurations both for the intra-subject and inter-subject cases are able to detect all of them. For other outlier types (such as turning around when walking), the optimal detection values have been obtained for the intra-user case (detecting all of the cases in the dataset in the case of turning around outliers). The inter-user case validation for the dataset in showed that there was a participant that was badly characterized when using the information from the rest of the users and the outlier detection did not provide good results independently of the selected similarity threshold.

REFERENCES

[1] O.D. Lara, M.A. Labrador, "A survey on human activity recognition using wearable sensors", In IEEE Commun. Surv. Tutorials, vol. 15 (no. 3) (2013), pp. 1192-1209

[2] A. Bulling, U. Blanke, B. Schiele, "A tutorial on human activity recognition using body-worn inertial sensors", In ACM Comput. Surv, vol. 46 (no. 3) (2014), p. 33

[3] J. Wang, Y. Chen, S. Hao, X. Peng, & L. Hu, , "Deep learning for sensor-based activity recognition: A survey". In Pattern Recognition Letters, vol. 119 (2019), pp. 3- 11.– Elsevier

[4] H. F. Nweke, Y. W. Teh, M. A. Al-Garadi, & U. R. Alo, "Deep learning algorithms for human activity recognition using mobile and wearable sensor networks: State of the art and research challenges". In Expert Systems with Applications, vol. 105 (2018), pp. 233-261. [5] T. Sztyler, & H. Stuckenschmidt, . "On-body localization of wearable devices: An investigation of position-aware activity recognition". In 2016 IEEE International Conference on Pervasive Computing and Communications (PerCom) (2016, March) (pp. 1-9). IEEE.

[6] Opportunity Dataset. 2012. Available online: https://archive.ics.uci.edu/ml/datasets/OPPORT UNITY+Activity+Recognition (accessed on 9 April 2019).

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