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Activity Recognition and Order-based Anomaly Detection for Smart Homes

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Abstract. Sensors provide an unobtrusive way of collecting daily living activities data of users. With the advancement in the field of electronics, collection of sensor data has become easier and can be used to create smart systems to assist users. This paper presents a deep learning approach with two stages: activity recognition and anomaly detection. Different LSTM models are studied for activity recognition and recognized activities are used to detect the abnormal behaviour of the user based on the sequences generated by PrefixSpan algorithm. The performance of the approach has been evaluated on real smart home dataset collected by CASAS on the Aruba testbed for the duration of 8 months. . . .

Keywords: Activity Recognition, Anomaly Detection, Frequent Sequential Patterns, Smart Home

1 Introduction

The need for activity recognition in the smart home environment is due to the upsurge in the number of older adults living independently. Older adults are prone to Alzheimer's disease and other forms of dementia. People affected by these conditions tend to forget their daily activities. Smart home environments can help detect early signs of such diseases and enable remote health monitoring by observing the activities of the residents and detecting users' behaviour. Activity monitoring can be enabled using various video, ambient, and wearable sensors.

Activity recognition has been a very trending research topic due to the advancement in IoT technologies and easier smart home deployments. Activity recognition results can also be used for other applications such as anomaly detection, fall detection [1], or theft detection. This work extends activity recognition by detecting anomalies for the recognized activities. The detection of deviation in a user's behaviour is called anomaly detection. There are two major classes of behavioural anomalies: duration-based anomaly and order-based anomaly. If a user spends more time in the toilet or sleeps less than usual, it is called a duration-based anomaly. In contrast, if a user goes to the toilet before sleeping or takes medicine after eating every day but does not follow the pattern in an instance, it is called an order-based anomaly [2]. Various contexts in a smart home environment like the time and the location of the activity being performed can also be considered while detecting an anomaly in users' behaviour. Anomaly detection can be used in various applications, such as reminding users of their tasks based on learning their activity patterns.

Monitoring the user activities using video sensors might hinder everyday tasks and intrude on the user's privacy. So, this work uses the ambient sensor data from the smart home environment to monitor a user's activities. Collection and processing of ambient sensor data can be challenging as they provide minimal information about the environment. For that reason, raw sensor events must be annotated to be used for learning the activities, which makes collecting extensive data challenging. There are several open annotated datasets available that are widely used among researchers.

This paper focuses on recognizing the activities of a user based on the sequence of sensor events and detecting order-based anomalies for recognized activities. Various machine learning and deep learning models have been developed for the activity recognition task. Studies show that deep learning models perform better for the activity recognition task [3]. Deep learning models for time-series sequential activity classification such as Long Short-Term Memory networks (LSTM), bidirectional LSTM, and an ensemble of unidirectional and bidirectional LSTM for activity recognition are studied in this work. The sequence of activities generated from ensemble LSTM is used to detect anomalies based on the order of the activities using the original sequences as the ground truth. PrefixSpan algorithm is used to generate the frequent sequential pattern for original activity sequences. An annotated dataset collected by CASAS Aruba [4], [5] containing the sensor readings of a resident performing sequential activities is used to learn the recognition model. The performance of the recognition models is evaluated based on the accuracy of the testing process. The dataset used has an imbalanced number of activity instances for each activity. As it is time-series real-world data, synthetic methods of balancing the data cannot be used. For this reason, the F1 score is also calculated for the performance evaluation. An anomaly rate is calculated to evaluate how a user behaves in the smart home.

This paper studies different recognition models and an anomaly detection approach for the Aruba dataset. The first section introduces the problem statement; the second section discusses the related works in the area of study; the third presents the architecture of the work, the dataset used, and the pre-processing of the dataset. Section four describes the algorithms used. Section five provides the results, followed by the conclusion and the further scope of the study.

2 Related Works

Many machine learning and deep learning models have been studied for activity recognition and abnormal behavior detection for daily life activities. Smart home environments are deployed to collect sensor data of daily activities performed by the residents and are very popular nowadays as they are privacy-compliant [6]. Multiple kernel Support Vector Machine (SVM) approach is applied in [7] for activity recognition, while the comparison research of the Gaussian mixture models, density-based clustering, and self-organizing maps is carried out in [2]. [8] proposes three methods; segmentation clustering, LRS algorithm and a hybrid unsupervised methods; for activity recognition from sensor data. In [9], an FSM-based approach is proposed for recognizing interleaved and concurrent activities. The study in [4] shows that generic models can be trained for daily tasks that span different environment settings and residents. Deep learning improves performance over conventional pattern recognition methods by automatically learning high-level representations of sensor data while reducing reliance on hand-crafted feature extraction [3]. Deep Belief Networks (DBNs) with many layers built using many Restricted Boltzmann Machines (RBMs) [10], different variations of LSTM models [11], a probabilistic neural network [12], deep neural networks [13] are used for activity recognition. [14] proposes an ensemble learning approach for activity recognition using smartphone sensor data that comprises a Deep Neural Network (DNN), a Convolutional Neural Network (CNN) stacked on the Gated Recurrent Unit (GRU), and a GRU. This work analyses LSTM models as they work best for the classification using time-series sensor data for recognizing the activity.

Using deep learning models eliminates the need for feature extraction, but hyperparameter tuning is required to ensure the model's performance. Isudra [15] employs Bayesian optimization to select hyperparameters, detector algorithms, features, and time scales and introduces a warm-start method to reduce optimization time for similar problems. Grid search and evolutionary algorithms can also be used for hyperparameter tuning. This work selects the hyperparameters based on the model and experimentations, and the best-trained model is saved for recognizing the activities.

Various machine learning and deep learning techniques such as SVM [16], Self-Organizing Maps [17], H2O autoencoder [12], and an overcomplete-deep autoencoder [13] are employed for anomaly detection. An alternative to complex machine learning algorithms is proposed in [18] based on the sequence pattern of activities for detecting anomalies in the daily sequences of activities performed. Box plots of duration and the number of subevents in the activity are used to generate the ground truth of the anomalous activities [10]. This work mines the frequent order of activities using the PrefixSpan algorithm to generate the ground truth and detect anomalies for the recognized activities.

Activity recognition based on the motion and door sensor states using LSTM, Bidirectional LSTM, and Ensemble LSTM is studied in this paper. The recognized sequence of activities is utilized to detect anomalies in the user behaviour using the PrefixSpan algorithm by generating frequent patterns of activities.

3 Proposed Architecture

Fig. 1 shows the proposed architecture. It mainly consists of two stages:

1. Activity recognition using unidirectional LSTM, bidirectional LSTM and ensemble LSTM
2. Anomaly detection using PrefixSpan generated sequences for original data and the predicted activity sequence from stage 1.

[scale=0.6]Arch4.png

Fig. 1. Architecture Diagram.

3.1 Dataset Description

Smart homes provide precise information and ensure monitoring without affecting the user's lifestyle. Vision-based data collection methods might intrude on the privacy of the user. This work uses non-vision-based sensor data for analyzing the activities of the user.

The dataset used in this work is the real-world sensor data collected by the Center for Advanced Studies in Adaptive Systems (CASAS) facility of Washington State University. The Aruba dataset contains activity records for older women for 220 days. The sensors deployed and used to collect data from the smart home are motion sensors, door sensors, and temperature sensors.

3.2 Data Preprocessing

The data is pre-processed for Activity recognition and PrefixSpan. The purpose of pre-processing the data is to make it compatible with the model and to remove unnecessary noise. The following types of noise are removed from the data generated from the smart home.

1. The activities that occurred rarely are removed. Respirate activity, occurring only six times in the dataset, was removed.
2. Some activities occurring multiple times consecutively are treated as duplicates and are removed.

Activity Recognition Activity recognition can be performed using several different input vectors. In this work, sensors and the state of the sensor as time-series data are used. Sequence classification methods can be used to classify activity based on time-series real-time data. Activity recognition, in this work, is performed using the sensor and sensor status sequence to classify the activity. LSTM models are most popular for classification using sequence data. The input vector with the sensor id and status is constructed for training the LSTM model for activity recognition. The sensor events of motion sensors and door sensors are used for activity recognition in this work. Initially, sensor event vectors are generated for each sensor event. Sensor event vectors have dimensions (number of sensor events, number of sensors). In our dataset, there is a total of 34 motion and door sensors, so that the dimension will be (n,34). The values of the sensor event vector will be the sensor state in the given sensor event. For motion sensors, the states can be ON or OFF, while for door sensors, the sensor states can be OPEN or CLOSE. States ON and OPEN are represented as binary '1' and OFF and CLOSE as binary '0' in this work. The resultant sample sensor event vector is shown in Table 1. Then activity vectors for each activity instance are generated. There will be a series of sensor events for an activity. In an activity vector, a sequence of sensor events for an activity is generated, and activity labels are one-hot encoded. Sample activity vector is shown in Table 2. The activity vector will then be given as an input for training the sequence classification model. Generating the vectors is for a better understanding of user behaviour.

Table 1. Sensor event vectors

2***Event**	**Sensors**						2***Activity**
	S_1	S_2	S_3	S_4	...	S_{34}	
E_1	0	0	0	0	...	0	Sleeping
E_2	0	0	1	0	...	0	Sleeping
E_3	0	0	0	0	...	0	Sleeping
E_4	0	0	1	0	...	0	Sleeping
E_5	1	0	1	0	...	0	Sleeping

Table 2. Activity vectors

Sensor events	**Activity (one-hot encoded)**
$[E_1, E_2, E_3, ..., E_k]$	[0, 1, 0, ..., 0]
$[E_{k+1}, E_{k+2}, E_{k+3}, ..., E_l]$	[1, 0, 0, ..., 0]
$[E_{l+1}, E_{l+2}, E_{l+3}, ..., E_m]$	[0, 0, 1, ..., 0]
$[E_{m+1}, E_{m+2}, E_{m+3}, ..., E_n]$	[0, 0, 0, ..., 1]

PrefixSpan PrefixSpan algorithm is used for frequent pattern mining. In this work, PrefixSpan generates a record of activity sequences that take place in a specific order frequently. PrefixSpan takes as an input a set of sequences of activities. The sequence of activities is extracted from the dataset without disturbing the order as the time-series data is used. Then shorter subsequences of length four are generated using a sliding window. These subsequences form the input of PrefixSpan, and the frequent activity orders are mined, which will be used to detect anomalies in user behaviour.

4 Algorithm

4.1 Activity Recognition

Activities are recognized using a variety of LSTM models for sequence classification. The deep learning models studied in this work are Unidirectional LSTM, Bidirectional LSTM, and Ensemble LSTM.

LSTM network is an extension of Recurrent Neural Networks. RNNs can work well for short-term dependencies in the data but not so well for the real-world time series data. LSTM will store states and have gates in addition to the features of RNN, enabling learning and predicting more complex long-term dependencies.

The unidirectional LSTM model comprises an input, a hidden, and an output layer. Sensor inputs are given to the input layer, and the dense output layer classifies the activity label. The hidden layer comprises one LSTM layer. The number of neurons and the learning rate are the common hyperparameters tuned to optimize the performance of the LSTM model.

Bidirectional LSTM is an extension of the unidirectional LSTM network. Bidirectional LSTM consists of one additional LSTM layer in its hidden layer. In the additional LSTM layer, the input sequence iterates in a backward direction, thus extracting patterns from the past and the future.

The Ensemble LSTM combines the output of Bidirectional and Unidirectional LSTM to predict human activity. There are various ways to create an ensemble model, such as addition, multiplication, average, and concatenate. In this work, the outputs of bidirectional and unidirectional LSTM models are concatenated, and then a dense output layer is added, which classifies the activity.

4.2 PrefixSpan Algorithm

PrefixSpan (Prefix-projected Sequential pattern mining) algorithm is a sequential data mining algorithm used to find frequent sequential patterns in the data [19]. The PrefixSpan technique only uses frequent prefixes when projecting a sequence database because frequent subsequences can always be identified by extending frequent prefixes, which significantly minimises the effort required to generate candidate subsequences. The sequence of activities is given as an input to the PrefixSpan algorithm to generate the frequent sequences of activities and the count of those sequences. If a sequence is encountered, it is checked against the frequent sequences generated by the PrefixSpan.

4.3 Anomaly Detection

Anomaly detection is used to find the deviation in the pattern. It is used in many areas, such as networking and fraud detection. Here, in this work, anomaly detection is used to detect deviating behaviour of the smart home user. Initially, the activity is recognized based on the sensor events sequence. Then, the frequent sequence patterns of activities for annotated data are generated. The next step is to detect the anomaly. For anomaly detection, we need to pre-process the output of the recognition model to generate a set of subsequences of length 4 for the recognized activity sequence using a sliding window. Then, we will check if the subsequence obtained from the recognized activity sequence is frequent in the original data. If it is frequent, it will be classified as a normal activity sequence; else abnormal.

5 Results and Discussion

Different LSTM models have been studied in this work. Unidirectional LSTM and bidirectional LSTM models have four layers. First is the input layer with shape (x, y), where x is the padded length of the number of sensor events for each activity and y is the number of sensors involved. The second layer is the LSTM layer for unidirectional LSTM and the Bidirectional and LSTM layers for bidirectional LSTM. The number of neurons of the LSTM layer is chosen based on the following formula.

$$N_h = \frac{N_s}{(\alpha * (N_i + N_o))} \tag{1}$$

where,
N_i = number of input neurons,
N_o = number of output neurons,
N_s = number of samples in the training data and
α = scaling factor usually between 2 and 10.

For different N_h values calculated for different α values, the optimal model is selected based on the resulting validation loss.

Next is the dropout layer with a frequency of 0.5 at each step to prevent overfitting. The dense layer forms the output layer of the model with the number of nodes same as the number of activity classes and softmax activation function. For multi-class classification, the softmax activation function gives the best results. Following is the softmax function.

$$\sigma(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \quad for\ i = 1, 2, \ldots, K \tag{2}$$

where,
σ = softmax function,
z_i = input vector,

e^{z_i} = corresponds to standard exponential function for input vector,
K = number of classes in the multi-class classifier, and
e^{z_j} = standard exponential function for output vector.

For ensemble LSTM, bidirectional and unidirectional LSTM models are concatenated using concatenate layer, and a dense layer is added as an output layer with the number of nodes same as the number of activity classes and softmax activation function.

Hyper-parameters are tuned for the models under study. Models are constructed using the Adam optimizer with a learning rate of 0.001 and a categorical cross-entropy loss function. For each epoch, models are check-pointed, and only the best model is saved based on the accuracy of the validation.

The metrics used for evaluating the performance of the models used for activity recognition are accuracy and F-measure. Bidirectional LSTM gives better accuracy and F1 score as compared to unidirectional LSTM, while ensemble LSTM outperforms both unidirectional and bidirectional LSTM models as shown in Table 3.

Table 3. Activity Recognition performance metrics

	Accuracy	***Precision***	***Recall***	***F1 score***
Unidirectional LSTM	69.66%	63.90%	69.66%	62.64%
Bidirectional LSTM	78.76%	71.45%	78.76%	74.28%
Ensemble LSTM	92.03%	89.40%	92.03%	90.65%

The normal and abnormal activities are detected for recognized activities using the PrefixSpan algorithm. Subsequences for the original and the recognized activity sequences are generated with a sliding window size of 4. The original activity subsequences are used in the PrefixSpan algorithm to generate the frequent sequence pattern and are used as the ground truth. "prefixspan" library of python is used to implement the algorithm in this work. If a recognized subsequence is a frequent sequence in the original data, it is classified as a normal sequence of activities. Otherwise, that sequence is classified as an anomalous activity sequence.

In this experiment, activity sequence [Leave_Home, Enter_Home, Leave_Home, Relax] is considered anomalous as the only possible activity following [Leave_Home, Enter_Home, Leave_Home] can be Enter_Home which is present in the original frequent activity set. [Leave_Home, Enter_Home, Leave_Home] sequence followed by any activity other Enter_Home will be classified as an anomaly.

The anomaly rate is calculated to evaluate the performance of the order-based anomaly detector. Anomaly rate is the number of anomalous sequences encountered for the total number of sequences. Out of 786 subsequences of the recognized activity sequence with size 4, 704 are classified as normal activity sequences and 82 as anomalous activity sequences, which gives the anomaly rate of 10.43%.

6 Conclusion and Future Work

The unidirectional LSTM, bidirectional LSTM and the ensemble model of both for recognition of activities based on the sensor events are studied in this work. The results show that ensemble LSTM model outperforms both unidirectional and bidirectional LSTM models. Further the recognition results are used for detecting anomaly in the user behaviour using PrefixSpan algorithm by generating frequent sequential patterns for actual activity sequences and comparing it with recognized activity sequence. This work is focused on detecting order-based anomalies and it can be extended by detecting both order-based and duration-based anomalies. Also, the dataset used for this work has the sensor data of smart home where one resident is living and performing sequential activities. Future works can study the results of these models for multi-resident setup and for more complex set of activities.

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