Echo State Network for Occupancy Prediction and Pattern Mining in Intelligent Environments

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Abstract. Pattern analysis and prediction of sensory data is becoming an increasing scientific challenge and a massive economical interest supports the need for better pattern mining techniques. The aim of this paper is to investigate efficient mining of useful information from a sensor network representing an ambient intelligence environment. The goal is to extract and predict behavioral patterns of a person in his/her daily activities by analyzing the time series data representing the behaviour of the occupant, generated using occupancy sensors. There are various techniques available for analysis and prediction of a continuous time series signal. However, the occupancy signal is represented by a binary time series where only discrete values of a signal are available. To build the prediction model, recurrent neural networks are investigated. They are proven to be useful tools to solve the difficulties of the temporal relationships of inputs between observations at different time steps, by maintaining internal states that have memory. In this paper, a special form of recurrent neural network, the so-called Echo State Network (ESN) is used in which discrete values of time series can be well processed. Then, a model developed based on ESN is compared with the most popular recurrent neural networks; namely Back Propagation Through Time (BPTT) and Real Time Recurrent Learning (RTRL). The results showed that ESN provides better prediction results compared with BPTT and RTRL. Using ESN, large datasets are learnt in only few minutes or even seconds. It can be concluded that ESN are efficient and valuable tools in binary time series prediction. The results presented in this paper are based on simulated data generated from a simulator representing a person in a 1 bed room flat.

Keywords. Sensor network, Time-series mining, Activity monitoring, Echo state network, intelligence environment

1. Introduction

The Sensor network has become one of the most important technologies for the 21^{st} century. It is a network consisting of spatially distributed independent devices using different sensors to monitor physical or environmental conditions at different locations. Sensor networks have been used in many applications like environmental monitoring building and structures monitoring, military sensing, physical security traffic surveillance, video surveillance, distributed robotics and similar [1]. The main goal of a sensor network is to

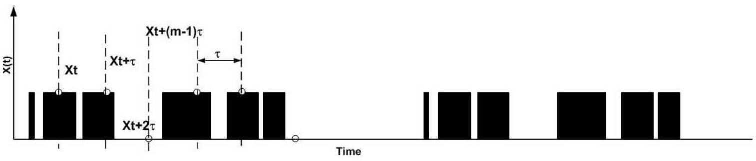

Figure 1. Discrete values of time series data collected from a door sensor

collect information in an intelligent environment. Sensor data from such an environment can be represented and mined as sequences or as time series data. These sequences are represented by a series of sensor values. All the sequences are ordered in time and occur sequentially one after another. However, for some applications it is not only important to have a sequence of these events, but also a time when these events occur.

The sensory data investigated in this paper represents the movement pattern of an occupant in an ambient intelligent environment. They are sequences of an ordered set of movements between one room and another inside a certain property, i.e. when the sensor is an on or off. The problem arising here is how one can process this huge amount of time series data and predict the next step in the series in order to extract important daily patterns from them. Figure (1) illustrates sensory data collected from a door sensor. This signal is a binary time series data where series $x(t)$, $x(t+\tau)$, $x(t+2\tau)$, $\ldots$ $x(t+(m-1)\tau)$ can be used as input variables to forecast the target variable $x(t)+m\tau$, for all $t=1, 2, \ldots\ n$ and a time delay length (τ).

To learn the pattern of the data series, Recurrent Neural Networks (RNNs) are used in which recurrent loops provide the network with some memory and thus with the ability to deal with the related time data. More specifically, we use the Echo State Network (ESN) approach. ESN is an efficient way to use RNNs where can obtain a computational power comparable to state of art of RNNs with a much simpler training algorithm and can be guaranteed to find the global optimum. It has shown that ESN learning algorithm can successfully used in an intelligent environment. The paper is organized as follows: section 2 briefly introduces ESN. Experimental results of ESN application in an intelligent environment are discussed in section 3. Finally, pertinent conclusions are drawn in section 4.

2. Echo state Network

In this section, the recurrent neural network, Echo State Network (ESN) is described. It was developed recently by Jaeger [2]. The basic architecture of ESN is illustrated in Figure (2) which consists of three layers. These include input, hidden and output layer. The input layer is connected to the hidden layer. Both the input and hidden layer are fully connected to the output layer. On the other hand, the output layer is backward connected to the hidden layer only. It is a discrete- time, continuous state where the activation function for all neurons is the sigmoid function [3].

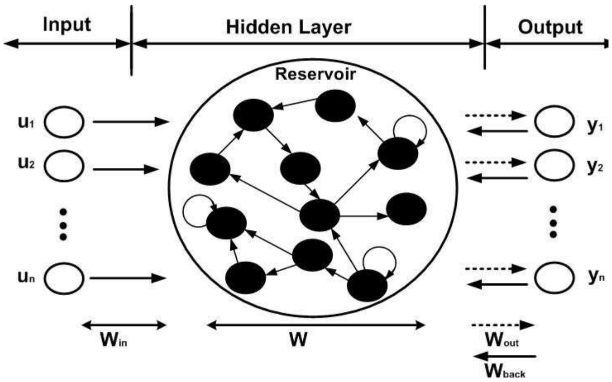

Figure 2. Structure of an Echo State Network approach. Only the output weights W$_{out}$ are adapted, all other weights (input, reservoir and feedback) are chosen randomly.

An ESN consists of a reservoir of conventional processing elements, which are recurrently interconnected with untrained random weights, and a readout (output) layer, which is trained using linear regression methods. The key advantage of the ESN is its ability to model systems without the need to train the recurrent weights [4]. For training an ESN with an input $u(n)$, a reservoir state $x(n)$ with M processing elements, and an output $y(n)$, the equations are calculates as follows:

$$x(n+1) = tansig(w_x.x(n) + w_{in}.u(n) + v(n+1)) \tag{1}$$

$$y(n) = w.x(n) \tag{2}$$

where $x(n)$ denotes the hidden layer or the internal state. The input and output to the ESNs are denoted by $u(n)$ and $y(n)$ respectively. tansig denotes hyperbolic tangent sigmoid function which is applied element wise, $v(n+1)$ is an optional noise vector. w_x, w_{in} and w are respectively the internal connection weights of the reservoir, the input weights to the reservoir and the readout (output) weights from the reservoir[5].

The ESN approach differs from other methods in that a large RNN is used (on the order of 50 to 1000 neurons) and in that only the synaptic connections from the RNN to the output neurons are updated i.e. weights coming from the hidden layer (also called reservoir) to the output layer are updated in order to achieve the learning task. As a result, large datasets are learnt in only few minutes or even seconds [2]. Also, there are neurons in the reservoir connected in loops [see Figure 2], therefore the past states 'echo' in the reservoir. The convergence of training in ESN is much faster than other RNN. This has made of ESN as an attractive model for a wide range of signal processing and control applications (e.g. time series prediction, pattern generation, event detection and classification and nonlinear control). For instance, in prediction of chaotic time series, ESN has proven to be a very efficient and valuable tool. The prediction is accomplished using a black box model, i.e. it only depends on past data since no further information is used.

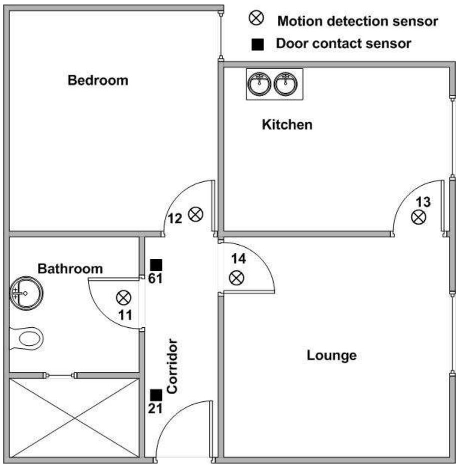

Figure 3. The flat layout

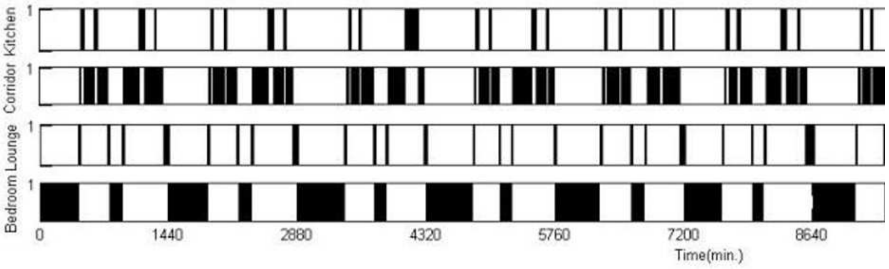

Figure 4. The occupancy Chart

In addition, no explicit model is given in order to create a new situation [6,7].

In this paper, ESN is used as a model to predict and extract behavioural patterns while keeping learning complexity at a low level. In addition, ESN is a very good choice for the modelling because in the methodology of the sensor networks, the new data are arriving at any time, whilst other approaches need all data input at the same time steps in order to compute the output.

3. Experiment Results

In our experiment results, ESN with different reservoir sizes are compared with the most popular recurrent neural networks: Back Propagation Through Time (BPTT) and Real Time Recurrent Learning (RTRL).

3.1. Intelligent Environment and Data Collection

In this section, sensor data collected from a smart environment are considered. The data collection system consists of an array of motion sensors which collect information us-

Table 1. Raw Sample of Sensor Data

Date	Time	Sensor ID	Sensor Value
14/05/2008	08:01:34	12	1
14/05/2008	08:01:35	12	0
14/05/2008	08:05:14	12	1
14/05/2008	08:05:15	12	0
14/05/2008	08:05:33	12	1
14/05/2008	08:05:34	12	0
14/05/2008	08:05:36	12	1

ing passive infra-red (PIR) sensors and door switches. In these situations, these sensors and door switches are used to record the behaviour of an elderly person, and allow the carer to observe any changes to patterns or specific incidents such as going outside at odd times. Our dataset is based on a single inhabitant living in a flat. The layout of the environment where the sensory data is collected is shown in Figure(3). The environment equipped with sensors will return the occupancy chart which records the daily activities as illustrated in Figure (4). This chart represents a single occupant only. The collected sensory data are discrete i.e. binary representing presence or absences from the environment. When the person moves from one room to another, the status of the sensor will vary. The environment consists of a lounge, kitchen, corridor, and bedroom. Therefore four sensors are deployed all around that observe the inhabitant motion. In addition, simulated data [1] have been created by a generator to validate our approach.

Each time stamped data item is characterized by specific properties. In table 1, a sample of raw data collected from a door sensor is illustrated, named as sensor 12. Our initial investigation is based on the data collected from a simulator based on the environment reported above. The model has been trained based on 10 days of data and test the model on 3 days of activities.

These datasets have been trained in our prediction tools to forecast multi-step ahead. In section 3.2, the prediction is observed and compared with test data in order to report the results which include the accuracy and error in the observations.

3.2. Results

In our experiments, instead of using a separate ESN for each sensor, all available sensors are connected at the same time as inputs to these networks and compute the prediction of these sensors reading using the combined datasets from the single input prediction. The advantages of using just one ESN for all sensors are to reduce the amount of memory and computation time. In this case, the number of input and output units depends on the number of sensors, which is driven by the actual sensor value at time t. The output unit is the value of the same sensor at time $t + \tau$ with different hidden units (reservoir) sizes. A number of parameters are used in ESN learning algorithm. These parameters are: number of neurons in the hidden layer (N), the Root Mean Square Error (RMSE)

[1] Simulated datasets have been created using a simulator based on MATLAB developed by Javad Mohammad, a PhD student in the School of Science and Technology of Nottingham Trent University

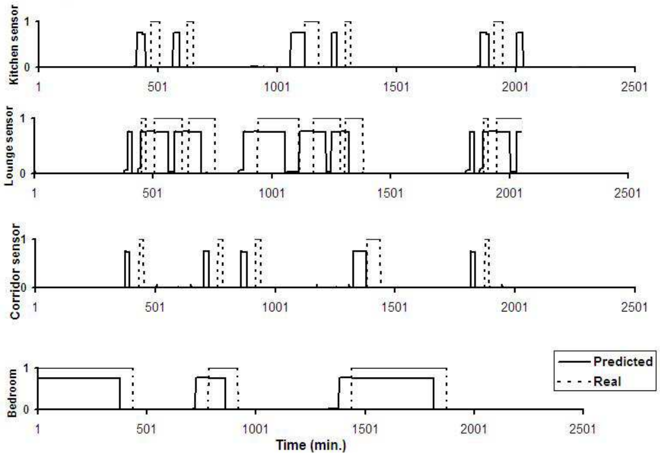

Figure 5. ESN results of 60 minute step ahead prediction of all sensors training datasets using 50 hidden neurons

for training and testing datasets, number of epochs and time required for training. To train ESN, simulated data generated by simulator were used. These data were split into training and test, e.g. the samples of 10 days are used as the training set and the samples of 3 days as the testing set. The analysis results of the echo state network for each sensor using 50 hidden neurons are depicted in Figure (5). In this figure a sample of two days is shown. This approach RMSE of about 5% for each sensor to predict 60 minutes step ahead.

Different sizes of reservoir (number of hidden neurons) are used to test the performance of ESN. It was observed that in ESN many datasets are trained in only few minutes or even seconds (see Figure (6)). Thus, the convergence of training in ESN is much faster than other RNN. Table (2) compares the results of all sensor datasets using ESN with the other recurrent neural networks techniques used in time series prediction. These techniques are back propagation through time and real time recurrent learning. ESN prediction results are better as compared with BPTT and RTRL in that the training time is significantly shorter. While the other approaches suffer from slow convergence as the number of neurons are increased.

4. Conclusions

The results presented in this paper show already that ESN is a very promising approach for a binary datasets collected from smart environments. Datasets investigated here are based on a single inhabitant environment equipped with appropriate motion sensors and door switches. Those sensors and door switches are used to record the behaviour of the occupant, and allow the carer to observe any changes to patterns. In addition, the neural network techniques have been compared to show their ability in prediction of binary time series data. It can be concluded that using large number of hidden neurons in ESN yielded a good results in terms of the error and time required for training and testing.

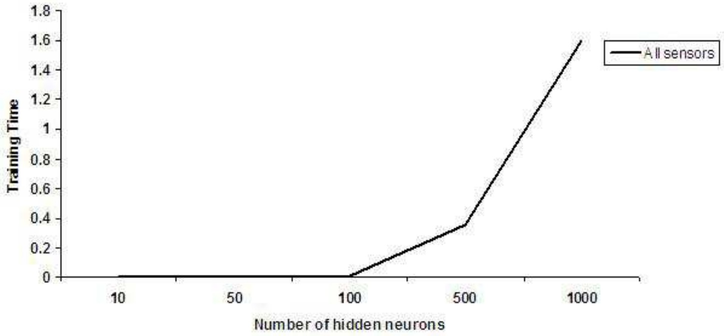

Figure 6. The training time (sec.) of all sensor datasets using different reservoir sizes (hidden neurons)

Table 2. Prediction results of all sensor datasets using ESN, RTRL and BPTT

Method	No. of hidden neurons	Training RMSE	Testing RMSE	Time(Sec.)
ESN	10	0.0556	0.0556	0.011581
ESN	50	0.0556	0.0556	0.051948
RTRL	10	0.0987	0.0964	281.823111
RTRL	50	0.0731	0.0740	1541.042739
BPTT	10	0.0759	0.0766	12.731490
BPTT	50	0.0803	0.0811	218.098591

In contrary to ESN, for other RNNs such as RTRL and BPTT, increasing the number of hidden (internal) units yields increasing the training/testing time.

A further direction for investigation is to implement ESN approach in a multiple occupancy situation, i.e. more than one occupant in a flat/home. This can be done by adding a different sensor to the network that can distinguish between occupants This task is complex, as not only must monitor the occupant, but it must also predict whether he/she alone or has visitors in a specific time. In addition, our experiments were done with simulated data, so the next step is obviously to implement ESN technique on-line with real data collected from sensors to extract the daily behaviour patterns.

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