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Predicting Activities of Daily Living of People Occupying Smart Environments

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Abstract

Aims/ objectives: To interpret the trends of Activities of Daily Living (ADL) and Activities of Daily Working (ADW) of people who are occupying Ambient Intelligence (AmI) environments and predict the next activities' time values. This research has two main contributions; A novel proposed technique called Activity Prediction Moving Average (APMA) based on Exponentially Weighted Moving Average (EWMA) and propose a new framework to be used in our research based on the Adaptive-Network based Fuzzy Inference System (ANFIS).
Study design: Cross-sectional study.
Place and Duration of Study: Department of Computer science, Institute of Science and Technology, between August 2018 and November 2018.
Methodology: Three datasets are included in this research of people who are occupying smart environments. These datasets are examined using APMA and ANFIS techniques.
Results: The results of the applied techniques show a good indicator of using them in human behaviour forecasting.
Conclusion: we investigated prediction techniques that can be applied to the human behaviours' data. The proposed solutions demonstrate the feasibility of interpreting this kind of data. These techniques will support the supervisor to get clear information about the situation of the participant who occupying a smart environment.

Keywords: Activities of Daily Living; graph theory; Exponentially Weighted Moving Average; Adaptive-Network based Fuzzy Inference System

2010 Mathematics Subject Classification: 53C25; 83C05; 57N16

1 Introduction

Smart Environments technology offer good opportunities to monitor participants. Recently, it is used in different aspects and applications such as in health applications and smart offices. The ultimate goal of this research is to enable supervisors who are using the AmI technology to monitor their participants and predict their situations based on recorded datasets. Using AmI technology will help

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the supervisor recognising any issue arises during the monitoring of their participants. For instance, the supervisor can recognise an abnormal disturbance happened in the sleeping time of a monitored person or the supervisor can expect an abnormal event that may happen based on forecasting the trend of a historical data of this person.

However, forecasting datasets of humans ADL is rarely investigated. It is hard task because of the nature of human's movements. Forecasting means extracting information from historical data and use them to predict trends and behaviour patterns. The unknown event of the future is often in the interest of the predictive analytic, but it can be applied to any of unknown events whether it be in the past, present or future Finlay (2014).

This research is conducted to investigate techniques of forecasting ADLs datasets and predict the direction of the trend of an ADL's behaviour trend. Moreover, our objective of this research is to detect the changes that may occur in the trend's direction of the ADL's behaviour that we are monitoring over time. By looking at the increased or decreased values of ADL's behaviour; we will notify the changes and then we can predict the direction of the trend of the ADL's behaviour.

Trends analysis is an essential to understand more clearly the processes in the current level of knowledge besides the capacity to create rapid changes on an unprecedented scale. However, the empirical approach of trend analysis is to look for relationships that could explain how the system works or to test hypotheses suggested by process-based considerations.

In particular, the trend Analysis is the preparation of collecting information and attempting to promotion a pattern, or trend, in the information. Although predict future events is often obtained by trend analysis, but trend analysis could be used to estimate uncertain events in the past, such as how many times the monitored person visited the toilet at the sleeping time in different days.

In this paper, collected ADL data are used to analyse people's activities that will help the supervisor to monitor and understand the human's behaviour. Therefore, it is very important to identify the monitored person's profile based on his/her ADL and behaviour. Recognising significant changes in human behaviour early will help the supervisor to take an action that can address prospective problems early as well.

This research primarily addresses trend analysis and prediction of human behaviour based on monitoring activities in smart environments. For example, by observing an elderly person's activity long-term, we should be able to help this person to live independently and be aware of his/her well-being according to trends observed in data that are collected from monitoring his/her ADLs. Another example, by monitoring a person in his smart office for long-term we can extract his/her daily pattern therefore we should be able to observe any change that may happen which will help the supervisor to recognise any abnormal activities.

This paper is structured as follows: in Section 2 some previous works are introduced; in Section 3 the trend analysis and prediction techniques that are applied to human activity recognition are presented. The results of the conducted experiments and the conclusions are presented in Sections 4 and 5 respectively.

2 Related Work

Prediction and Trend analysis for human behaviours that are monitored in AmI environments is rarely investigated; therefore, this research will raise important indicators to other researchers who are interested in this topic. However, some researchers mentioned a relative work to this area of research such as, Mahmoud el. al. in [Mahmoud and Akhlaghinia and Lotfi and Langensiepen (2011)] introduced the importance of trends in activities of daily living of a single elderly person. Veerbeek el. are seeking for the knowledge that can be used to predict outcome of ADLs that may paramount stroke management, and they find that the results of predictive is still unclear Veerbeek and Kwakkel and van and Ket and Heymans (2011). To search for regular patterns, highlighting the periodicity and variability of each discovered pattern, however, the datasets are used in this research to validate their algorithms are very small. Cook el.al. in Cook and Schmitter-Edgecombe and Dawadi (2015) used machine learning techniques are used to analyse ADLs of older adults to understand the impact of different medical conditions, and they claim that their classifier technique has an excellent accuracy.

Higgins el. al. in Higgins and Green (2008) presented a pattern mining model to monitor high-level activities of an elderly to help him lives independently, the system will send an alter to caregivers about the evolution of the behaviour status of their monitored user. Their idea is good, but they did not use their model on a real data . Authors in Kemp and Guara and Rednic and Brusey (2013) are introduced an algorithm to generate information and summarisation of changes in an elderly behaviour for a long-term monitoring. They focus on reducing the number of transmission required by wearable monitoring system. Suryadevara el. al. in Suryadevara and Mukhopadhyay and Wang and Rayudu (2013) introduce a framework to determine the wellness of an elderly, they use the double exponential smoothing strategy to determine the tends of the elderly's activity, however, they claim that the sequence pattern of the sensors on a particular day at a particular time period could be predicted using Sensors Activity Pattern Matching (SAPM) technique, which is not possible for human behaviours.

in another effort, Using a linguistic summarisation to describe long-term trends of change in human behaviour is presented in Ros and Pegalajar and Delgado and Vila and Anderson and Keller (2011), they introduce a procedure to provide information to elders, carers and family in an understandable language by adapting a measure the partition of similarity for comparing behaviours that are adapted over time. Their idea is based on clustering data and comparing the similarity between the activities in a specific time to detect trends, however, they are concentrating on linguistic summarisation more than trend analysis itself. Researchers in Forkan and Khalil and Tari and Foufou (2015) described models for detecting behavioural and health-related changes for a patient who is monitored continuously in a smart home. They are used Holt's liner trend method to predict different physiological parameters of the monitored user.

3 The Applied Prediction Techniques

In this research different techniques of prediction are investigated. These techniques are called from different disciplines. The investigated techniques are applied to datasets that are collected from monitoring an people who lives in a smart home or work in a smart office. Each data set represents an activity of daily living of each person in a specific place. The real datasets contain binary data which are representing indoor sensors such PIR, door contact switch, and pressure sensors. Tables 1 and 2 show examples of the stored datasets with date and time, sensor type, sensor value, and the location of the sensor.

Table 1: A sample of real data of smart home.

Date and Time	Sensor Type	Location
$2015-01-11\,11:04:17.656$	PIR	Living Room
$2015-01-11\,11:05:03.766$	PIR	Master Bedroom
$2015-01-11\,11:06:03.796$	PIR	Kitchen

The prediction techniques that are used in this paper are presented in the following paragraphs:

Table 2: A sample of real data of smart office.

Date and Time	Sensor Type	Location
$2016-02-07\,09:04:17.656$	Door Contact	Office Door
$2016-02-07\,09:04:18.766$	PIR	Light
$2016-02-07\,09:05:03.796$	Pressure	Chair

3.1 Activity Prediction Moving Average

The Activity Prediction Moving Average (APMA) has its foundation on the Exponentially Weighted Moving Average (EWMA) to predict the next value of the activity. In contrast to EWMA, it is used to analyse data points by creating series of averages. In brief, the EWMA gives different weights to data points at different positions. The EWMA can be an infinite impulse response filter that applies weighting factors which decrease exponentially and never reaching zero Holt (2004); Gardner (2006).

The EWMA for a series P may be calculated recursively using Equation 3.1, which can be expressed in technical analysis terms to show the steps of EWMA towards to the latest datum point, using a proportion of the different (each time).

$$EWMA_{new} = EWMA_{old} + \beta \times (P_{current} - EWMA_{old}) \tag{3.1}$$

where:

- The β represents the degree of weighting decrease, which is a constant smoothing factor between 0 and 1. A higher β discounts older observations faster.
- $P_{current}$ is the data value at current time.
- $EWMA_{old}$ is the old value of the EWMA.
- $EWMA_{new}$ is the new value of the EWMA.

$EWMA_1$ could be initialised in different ways; the most common way is by setting $EWMA_1$ to P_1. It could be initialised by using an average of the first 4 or 5 data points. It is very important to initialise $EWMA_1$ because its effect on the resultant moving average depends on β values. Choosing small values of β make the choice of $EWMA_1$ relatively more important than large β values. The higher β values will discount older observations faster. For more information read our previous paper Elbayoudi and Lotfi and Langensiepen and Appiah (2016).

3.1.1 The Proposed Algorithm(APMA)

Based on the EWMA we build a model that can be used to predict the next value of a single activity. The model is tested with our data sets and it shows good results in terms of estimate the next value of the activity. For instance, when it used to predict the five days of occupancy duration in an office, the APMA estimates these values of durations. The Algorithm 1 illustrates the procedure.

3.2 Adaptive-Network based Fuzzy Inference System (ANFIS)

The basic theory of ANFIS model is based on ifthen rules and several inputoutput parameters. Also, ANFIS are using training, learning algorithms of neural networks Jang (1993); Boyacioglu and Avci (2010). To clarify the explanations, we will assume that the fuzzy inference system has two inputs x and y and one output z and one of fuzzy models (we will assume a first order of Sugeno model). Then the typical fuzzy rule set $if\ then$ can be expressed as Equation 3.2

Algorithm 1 The Prediction Algorithm APMA.

procedure APMA
    Prepare the binary data to be a time series.
    Define training data T.
    Identify the number of data points that need to be predicted m
    Identify the weighted start value of β*.*
    repeat
        For time t, session m
        repeat
            Calculate EWMA for N data points for all data T
            Calculate the S the start point to predict first value of N ...
            based on historical n data points
            Use S to calculate the next value of N
            if N not accepted **then**
                Modify S and β*.*
        until all required sessions covered
    until all required time covered

$$IF\ x\ is\ A1\ and\ y\ is\ B1\ then\ f_1 = p_1x + q_1y + r_1 \tag{3.2}$$

where: p, r, and q are linear output parameters.

Figure 1 explains the architecture of ANFIS model that has two inputs and one output.

This ANFIS model is using five layers and nine ifthen rules as explained below:

- $Layer_1$: In this layer Each node i is a square node with a function represented in Equation 3.3

$$O_{1,i} = \mu A_i(x),\ for\ i = 1, 2, 3\ O_{1,i} = \mu B_{i-3}(y),\ for\ i = 4, 5, 6 \tag{3.3}$$

  where: x and y are the node i inputs, A_i and B_i are linguistic labels associated with inputs' nodes, O_{1_i} is the membership function of A_i and B_i. Also, it is common to choose $\mu A_i(x)$ and $\mu B_i(y)$ to be a bell-shaped with maximum equal to 1 and minimum equal to 0, which is represented in Equation 3.4

$$\mu A_i(x), \mu B_i(y) = exp(((x_ic_i)/(a_i))^2) \tag{3.4}$$

  where: a_i, c_i are premise parameters set.

- $Layer_2$: In this layer each node is shown in a circle labelled with which multiplies the received signals. The output of each node representing the firing strength of a rule. Equation 3.5 illustrate this procedure.

$$O_{2,i} = w_i = \mu A_i(x).\mu B_{i-3}(y)\ for\ i = 1, 2, 3...9 \tag{3.5}$$

- $Layer_3$: The nodes of this layer are shown in circles labelled with N. Each node calculates the ratio of the ith rules. Equation 3.6 explains the layer's processing.

$$O_{3,i} = \overline{w}_i = w_i/(w_1 + w_2 + ... + w_9)\ for\ i = 1, 2, 3...9 \tag{3.6}$$

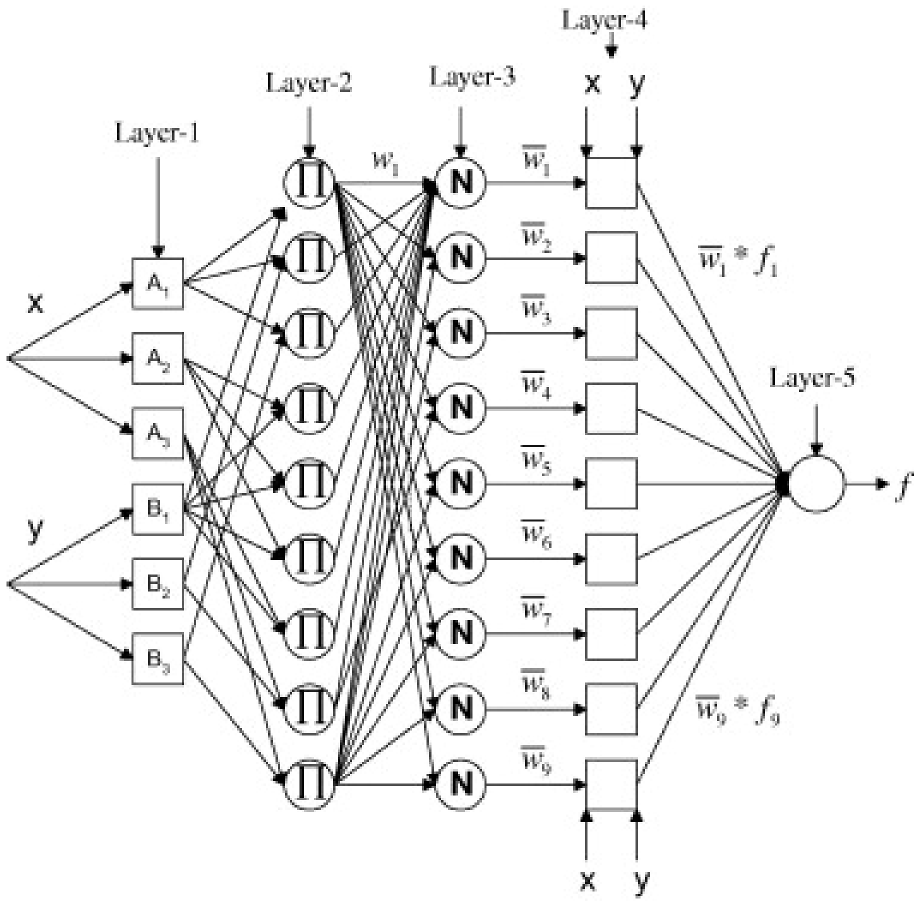

Figure 1: ANFIS Architecture Example.

- $Layer_4$: Equation 3.7 shows the function of each node in this layer. Also, every node is a square node.

$$O_{4,i} = \overline{w}_i.f_i = w_i.(p_1x + q_1y + r_1)\ for\ i = 1, 2, 3...9 \tag{3.7}$$

where: w_i is the output and p_i, q_i, r_i are consequent parameters.

- $Layer_5$: The last layer is represented by circle and labelled by $\sum$. It is computing the final output as shown in Equation 3.8

$$O_{5,i} = overall\ output\ = \sum_i \overline{w}_i.f_i = \frac{\sum_i w_i.f_i}{\sum_i w_i} \tag{3.8}$$

In this paper, the ANFIS model is used to predict the values of activities' trends of our datasets. Before using ANFIS there steps needed to be taken first. Figure 2 illustrate our proposed model diagram contents these steps. In addition, the input layer in ANFIS will receive datasets represent the values of trends of each activity we are examined. The output values should be the predicted values of the activities.

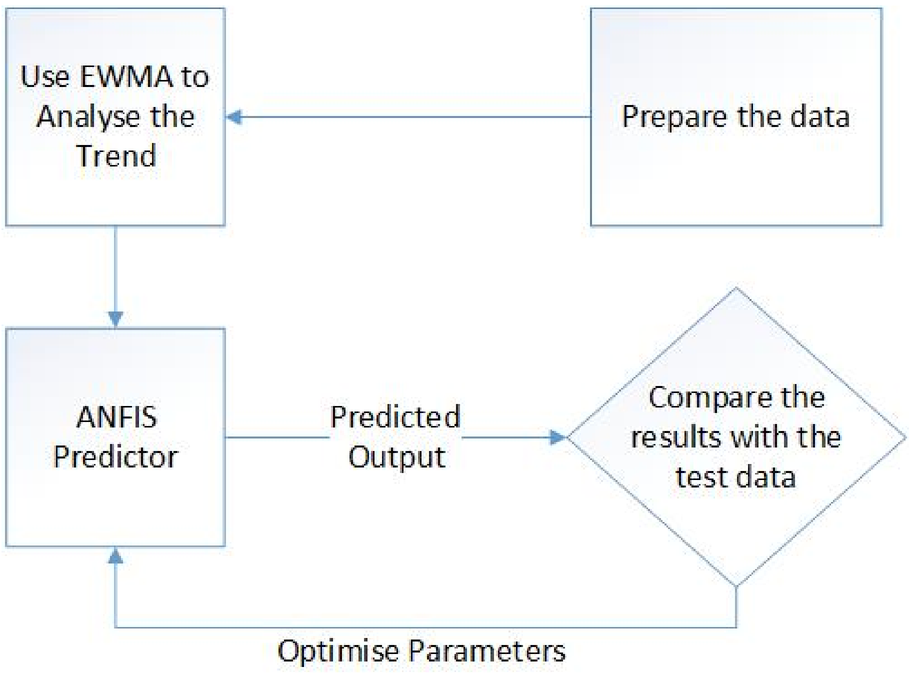

Figure 2: The Proposed Diagram Using ANFIS.

4 The Results

The results of the applied techniques are given a good indicator that they can be used in human behaviour forecasting. A brief discussion of our results in the following sections:

4.1 Results from APMA

APMA is proposed as a predictor model, it is tested using different type of datasets that are extracted from the original data to represent the duration of sleeping in the bedroom and the duration of occupying a smart office. We used the EWMA to detect the trend in our data first then we used it to predict extra data based on the data that are occurred from the trend. Two pairs of numbers are used to represent the fast and slow EWMA. This method will allow to see the trends of data in different degree of smoothing. In prediction process, it is very important to adjust the weighted value to gain the best results. The other fact in prediction is the smallest number of prediction days the better results will gain.

The first experiment was done with the data of sleeping duration. The $(7, 28)$ data points are used to compute EWMA. Then the APMA is used to predict the trend of last 7 days. Comparing between the results of using fast and slow EWMA, they show that the fast EWMA is more sensitive to changes that may happen in original data, and crossover occurs when data changes happens gradually up or down as it is shown in Figure 3. However, the same procedure is used with the office's data. The $(5, 20)$ data points are used to compute EWMA and then use the APMA to predict 5 days. With the same concept that is used in the first experiment Figure 4 shows the results.

On the other hand, by comparing the EWMA data and the APMA data we can see the significant results that we obtained by using APMA. the results in Tables 3, 4 shows how close the predicted

Table 3: A sample of results of using EWMA and APMA with data of the Bedroom.

EWMA data	APMA data
514.7019343	511.72
524.3639507	523.21
472.5271297	477.13
495.0536806	493.42
489.9819271	490.29
457.765612	460.72
446.6783757	447.95

Table 4: A sample of results of using EWMA and APMA with the Smart Office's data.

EWMA data	APMA data
384.80	384.36
396.39	393.99
406.01	403.61
390.245	392.91
396.676	395.92

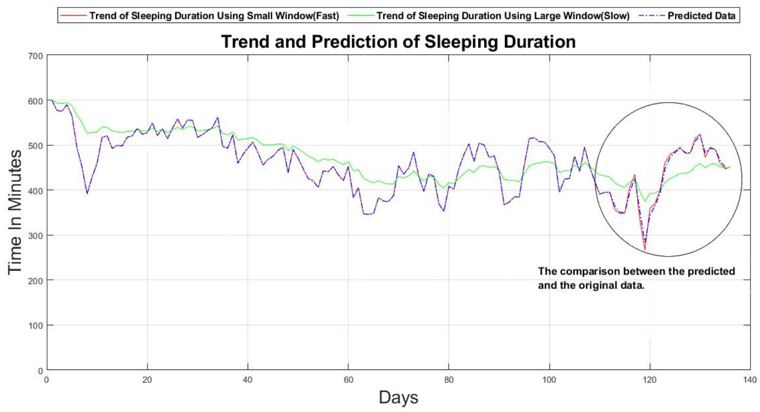

Figure 3: Trend and Prediction of Sleeping Duration EWMA.

data to the original one.

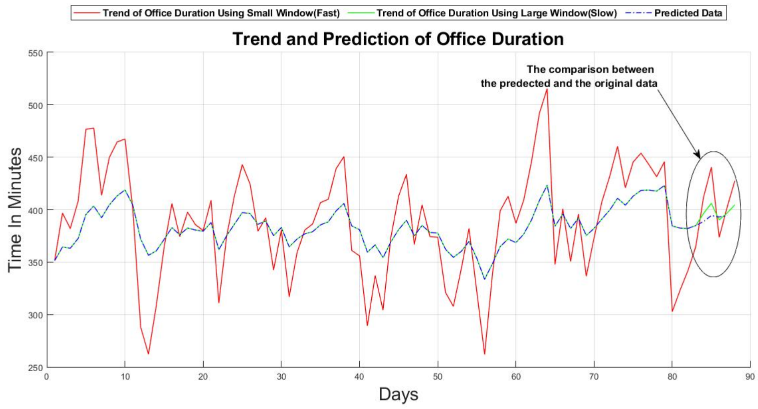

Figure 4: Trend and Prediction of Occupying an Office Using EWMA.

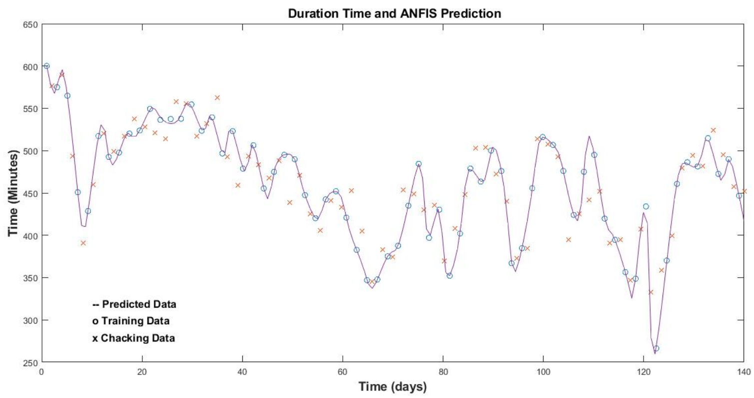

Figure 5: Results of the Prediction Using ANFIS for Duration Time.

4.2 Results of ANFIS

In this work, ANFIS is used to predict a value of activity based on historical data that we have. As it shown in our proposed model, it is essential to prepare the data to be used as a time series. As we believe in that, the original binary data is very hard to model or predict. The second step we done is using trend analysis technique to smooth each dataset and get its trend; then the time for ANFIS to predict the new values of data points based on the smoothed datasets. The variants of the algorithm used in the study are different numbers of membership functions and different types of function (i.e "gbellmf", "gauss2mf"). Different datasets are used in this work too.

Figure 5 represents a sample of our results of using ANFIS to predict our data. In this example, we used 30 membership function, type "gbellmf". Figure 6 shows the final membership functions that are used in this example. The dataset used here is for the duration of sleeping time in a bedroom. Table 5 presents a sample of our results, this table has two columns; one for actual data and the other is for predicted data. In addition, the root-mean squared (RMS) is used to compare predicted and actual values for model validation.

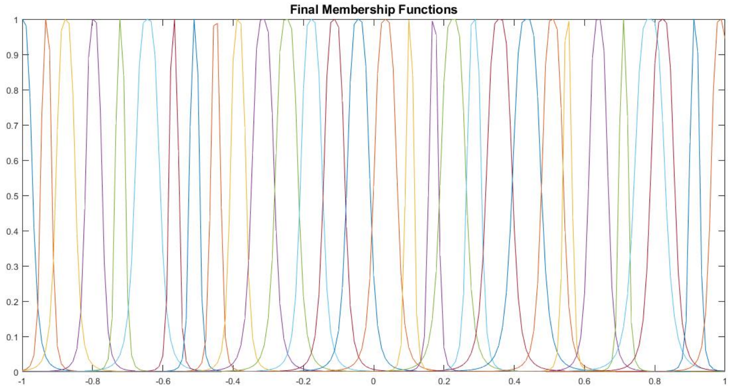

Figure 6: Final Membership Functions.

Table 5: A sample of results of using ANFIS with dataset of the Bedroom.

EWMA data	ANFIS data
451.65	479.12
494.67	492.18
481.95	489.84
457.76	458.02
443.10	451.65

5 Conclusions

In this paper, we investigated prediction techniques that can be applied to the human behaviours' data. The proposed solutions demonstrate the feasibility of interpreting this kind of data. These techniques will support the supervisor to get clear information about the situation of the participant who occupying a smart environment. The results of conducted experimenters give good indicator of the importance of using prediction techniques to interpret the humans' activities.

To use prediction techniques with such data we have; it is essential to prepare data first. Preparing our data includes; dealing with missing data, convert data from binary to the suitable format that we used later with prediction techniques and extract the exact data for each feature or activity.

The prediction techniques used in this paper present good results in terms of activity annotation. They can determine and predict the next situation or predict the orientation of the trend in each dataset. They can show more information for each sensor's uses in a specific time like the minimum usage duration, average usage duration and maximum usage duration.

We start this research using our novel algorithm AFMA to predict N data points alongside we use it as trend analysis technique. It presents good results in terms of prediction. Moreover, in contrast to using EWMA which is the best technique in order to detect trends in our data and because of its sensitivity to the changes in data, it shows that it has the ability to identify the concealed abnormal events.

ANFIS is the second technique that we used to predict new values of our datasets. It presents good results in terms of estimating new values of such data that we have. When using ANFIS with this kind of data, it is very important to smooth the data and optimise the number of membership functions.

Finally, by comparing the results of using these two techniques in terms of prediction, we can identify that AFMA can predict a small number of data points ahead and the more values we predict the more errors in the estimated data will occur. On the other hand, using ANFIS will give better results if the data is smooth and it will give less fine results if the data is more chaotic.

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