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Zaineb Liouane[1,2(✉)], Tayeb Lemlouma[2], Philippe Roose[3], Fréderic Weis[2], and Hassani Messaoud[1]

[1] LARATSI, Monastir University, Ibn El Jazzar, Monastir, Tunisia
liouane.zaineb@yahoo.fr
[2] IRISA, Rennes1 University, Rennes/Lannion, France
[3] LIUPPA/T2I, Pau and the Adour Countries University, Anglet, France

Abstract. Detect efficiently the activities of daily living of elderly people at home in order to provide a secure life and to intervene in the necessary time is an important problem we propose here an improved artificial neural network model. As we need an efficient prediction model, we propose a recurrent output neural network model (RO-NN) combined with a genetic algorithm (GA) which surely monitors and predicts the state of the concerned elderly person. Furthermore, we propose a prediction algorithm "Unusual Behavior Algorithm (UBA)" dedicated to detect the unusual activities and hold us account in the dangerous state.

Keywords: Unusual behavior algorithm · Recurrent output neural network · Genetic algorithm · Elderly people · Smart home

1 Introduction

The growing number of the aged person is remarkable in the recent years [1]. Consequently, the concept of smart home becomes very promising in the aim of providing solutions for elderly that respect their autonomy and their intimate life. Also, it is know that the behavior of the elderly is very sensitive then it is necessary to monitor and supervise the daily activities of the person in order to detect any unusual behavior. Functional tasks in the daily lives of older people are divided into two parts, ADL's and IADL's [2–4]. Activities of daily living (ADL) are the basic tasks of everyday life, such as eating, dressing, grooming, washing and unary function. The instrumental activities of daily living (IADL's) are the activities that people can do since they are awake, such as dressing, homework, phone use, etc. In this paper, we focus our thoughts to monitor the activities of daily living of seniors evolving in smart home environment. We propose an new algorithm, *Unusual Behavior Algorithm* (UBA), in order to detect any unusual and dangerous state in order to maintain the behavior of the person and to provide prevention. The proposed algorithm is based on the routine of daily activities, the routine duration of activities and the number of routine of elapsed activity. Thus, to monitor persons and to predict efficiently with great accuracy their behavior state, it is necessary to define an efficient prediction model. Various types of Artificial Neural Networks

A.M. Madureira et al. (eds.), *Intelligent Systems Design and Applications*,
Advances in Intelligent Systems and Computing 557,
DOI 10.1007/978-3-319-53480-0_73

(ANN) were used in the literature [5, 6], such as Multi-Layer Perceptron (MLP), Echo State Networks (ESN), Radial Basis Function networks (RBFN), Boltzmann Machine, etc. ANNs are used to apply case-based reasoning applications for intelligent homes. Some applications are elder care, health care and emergency solutions. The result of the recent researches shows that neural networks seem effective in different applications, for this reason, in this paper, we propose to improve a specific type of the ANN in the aim of providing a good prediction model. We propose a recurrent output neural network model (RO-NN) to predict the usual behavior of the monitored elderly. We also propose to integrate a genetic algorithm (GA) in the learning step in order to evolve the rate of accuracy. So, the output data of the model who are the basic data of UBA to detect the abnormal state. Our work is based on real data, which are the activities provided by a Functional Autonomy Measurement System (SMAF) profile P_1 of one monitored.

This paper is structured as follows: the next section presents the related works. In Sect. 3, we describe our proposed model, the RO-NN based on GA. Section 4, is devoted to the proposed algorithm (UBA). Section 5 presents the results of the implementation and the simulation of the RONN-GA. Finally, Sect. 6 concludes this work.

2 Related Works

In the context of smart homes literature, several works concentrate about the recognition activities models and methods in order to improve the quality of the monitoring. Most researches focus on the Artificial Neural Network (ANN) in order to evolve the recognition accuracy rate.

To monitor disabled people in their life, Hussein et al. [7] propose to use two types of Neural Network "the Feed-Forward Neural Networks and the Recurrent Neural Networks". The neural network testing results of [7], show the importance of the NN for prediction activities in a smart home. Teich et al. [8] build a *Stable Neural Network* (SNN) based on a feed forward neural network in learning step. The results show that a supervised feed forward neural network with multiple hidden layers gives a good result after a short training period. Fran et al. [9] use a back propagation neural network with a feed forward strategy in the learning process to recognize the Activities of Daily Living (ADL) in a smart home. Thus, [9], reveals that the bigger number of neurons in the hidden layer is, the more accurate the prediction is, however a large number of neurons may result in a large learning time. These authors deduce that the Back Propagation Algorithm (BP) neural network achieves good recognition accuracy. Stefan Oniga et al. [10, 11], design a complex assistive system based on ANN in order to improve the quality of human life, In [10], the authors concentrate on the recognition of the body posture, arm posture and usual activities. Zhigang Liu et al. [12], propose a mechanism for estimation of elderly posture based on BP neural network, these authors conclude that the BP algorithm has a high accuracy rate and robustness in the elderly posture recognition.

View the obtained results used by the ANN models in our work we investigate to propose a recurrent output neural network based on Genetic algorithm in the learning step to predict efficiently the usual behavior of our elderly in the aim to detect any behavior change using our proposed algorithm.

3 RO-NN Based on GA Model

3.1 Structure of the RO-NN

The architecture of the neural network typically consists of an input, a hidden layer and an output layer. Each node in those layers is linked using a weighted connection called weight (W) and a Bias (B) providing additional adjustable parameters of the model and the transfer function (f) that can have different forms (Log function, Tan hyperbolic function, Linear function, Radial basis function, sigmoid function, etc.) calculates the output (y). Therefore, we notice that a neuron network is characterized by a triplet (Weight W, Bias B and Transfer function f). In this paper, we propose a recurrent output neural network (RO-NN) model consists of one input layer, one hidden layer and one output layer, the simplicity of this architecture directly improves the speed of our model. To improve the prediction accuracy, we also include the recurrence notion, so that, the intervention of the previous output in each iteration in the input layer increase the rate of the accuracy.

The input data consists of the activities of daily living, a real data sets (more detail in the Sect. 4.1).

The output (the predicted data) depend on the lagged in inputs and in the following outputs

$$y(t) = f\,(x(t), x(t-1), \ldots\, x(t-N), y(t-1), \ldots\, y(t-M)) \tag{1}$$

y(t) denotes the predicted output expected at time *t*; *x(t)* is the real input; *y(t−1)* is the previous output; *f* is the nonlinear function, *N, M* is the input and the output memory orders. After the structure initialization step, RO-NN is characterized furthermore by two steps the learning and the validation. Learning step is necessary to perform the actual learning. It consists in adjusting weight and bias. It enables determining the best parameters of the model and performing a good prediction model. View the importance of the learning step of the RO-NN model and in the aim of evaluating the accuracy performance we propose to integrate a genetic algorithm (GA) in the learning step in order to perform a best learning parameters (W and B) [13].

3.2 Learning Algorithm of the RO-NN

Genetic Algorithms consist in heuristic search and optimization techniques that mimic the process of natural evolution [14, 15]. Genetic Algorithms implement the optimization strategies by simulating evolution of species through natural selection. GA work on a population of individuals instead of individual. At the beginning of the computation a number of individuals (the population) are randomly initialized. The Genetic algorithm model operates like natural processes such as selection, recombination and mutation. The first/initial generation is produced. After the data coding, the genetic-algorithm operators are applied [16, 17].

Selection Operator: Individuals are selected according to their fitness for the production of offspring. The primary objective of the selection operator is to emphasize the good solutions and eliminate the bad solutions in a population while keeping the population size constant.
Crossover Operator: Parents are recombined to produce offspring. Crossover is an operation that exchanges part chromosomes between a pair of parent individuals with a relatively large probability (crossover probability) and produces two new individuals.
Mutation Operator: All offspring will be transferred with a certain probability (mutation probability) this operator allows to introduce the novelty of the population.

However, there is no guarantee that the new offspring obtained will produce good solutions. The Genetic-algorithm operators continue until an optimal solution is found. If the optimization criterion is not satisfied, the creation of a new generation starts.

3.3 Concepts of the RO-NN Based on GA Model

This paper proposes to combine GA with RO-NN to form an improved prediction model.
The algorithm is formed by three steps:

Step 1: Determine RO-NN topology. Determine the number of input nodes, define the number of output neurons based on output parameters, and then define the optimal number of hidden nodes. Finally, we can get the individual length of GA.

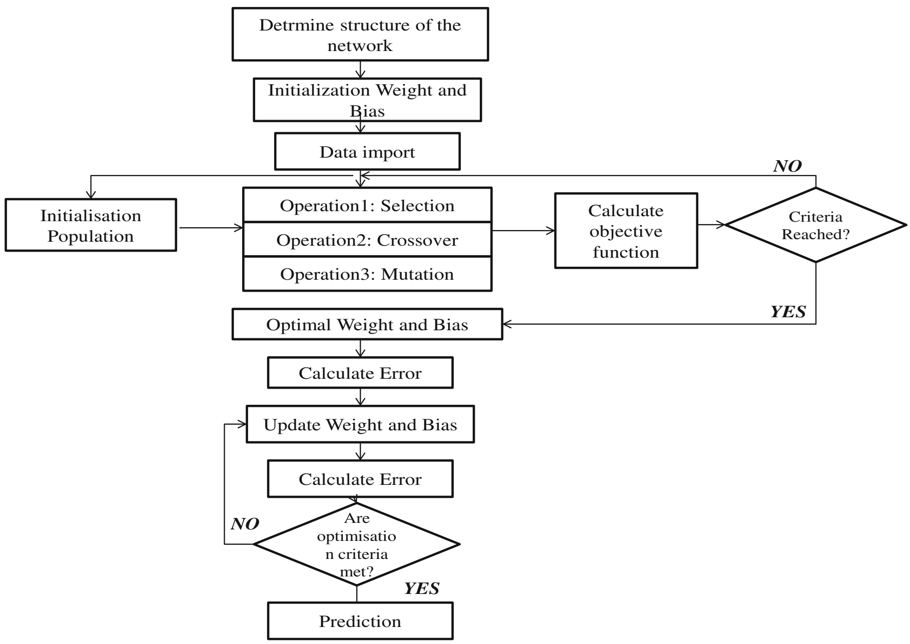

Fig. 1. The flow chart of RO-NN based on GA in the learning step.

Step 2: Utilize GA to optimize RO-NN weights and bias. Generate a population randomly; whose individual represents network weights and Bias. Then compute the fitness value through fitness function and find the best individual by selection, crossover and mutation operations.
Step 3: Use improved RO-NN to predict. Initialized with the best individual, RO-NN weights and Bias can be local optimized again during training. The optimized RO-NN can obtain an accurate prediction and an excellent efficiency.

The flowchart of combinational RONN–GA model is described in Fig. 1.

4 Unusual Behavior Algorithms

In this section we consider the abnormal behavior detection, thus the proposed algorithm based on the output data of the RO-NN who is the predicted data. So, from the predicted data, we will try to detect and identify the abnormal state of the elderly.

4.1 The Concerned Data

To ensure a secure life at home we must know all the routine activities of the occupant in order to be able to remotely recognize (without disturbing) unusual activities. In our work we focus on to monitor the activities of daily living of the elderly people to detect any presence of the unusual behavior. Activities of daily living ADLs are a basic self care tasks. They include eating, dressing, grooming, washing and unary function. In this paper, we use a real data collected from a health monitoring project" e-health monitoring open data project". These data concern the elderly in his smart home during one year. This database includes three parameters "starting time, ending time and activities" based on SMAF profile P1. In our work we are interested in the activities of daily living ADLs. Table 1 shows the ADLs with a specific code for each activity.

Table 1. The activities of SMAF profile P_1.

ADL	Activity	Code
Eating	Eating	1
Dressing	Dressing	2
Washing	Take a shower	3
Grooming	Washing hand/face	4
	Hair dray	5
	Move dish	34
	Make up	6
Unary function	It takes same toileting action	7

Figure 2 shows the usual scenario of the elderly during a week, each activity identified by a code is given in Table 1. The unusual scenarios of daily living is represented by any presence of changes in the daily living routine. So any perturbation in the routine activities indicates that our patient has a potential problem in those activities. Figure 2 shows four week scenarios (Week1, Week2, Week3, and Week4) of the monitored elderly. As we can notice, the structure of each week scenario is maybe different. However, this is not sufficient to identify with any certainty how many unusual states are in this period.

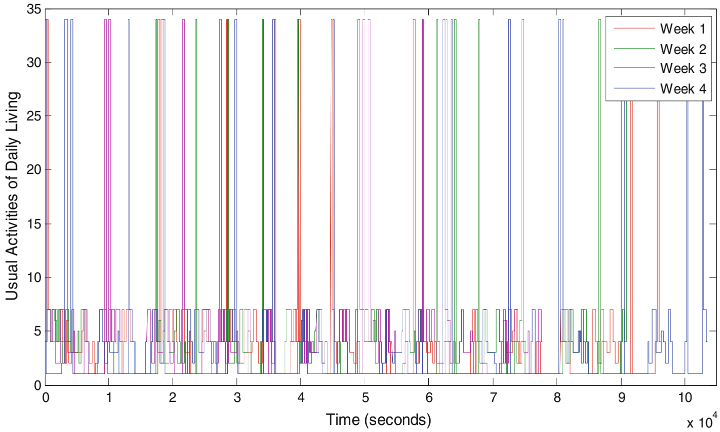

Fig. 2. The different scenarios of the activities by different week.

Sometimes the perturbation of the usual activities indicates a perturbed state of the person all depends on the disturbances of the activity duration. So in our work we propose to take care on the routine duration of each activity. Figure 3 shows the routine number of each elapsed activity by week during a month in the aim to know approximately the routine number of each activity.

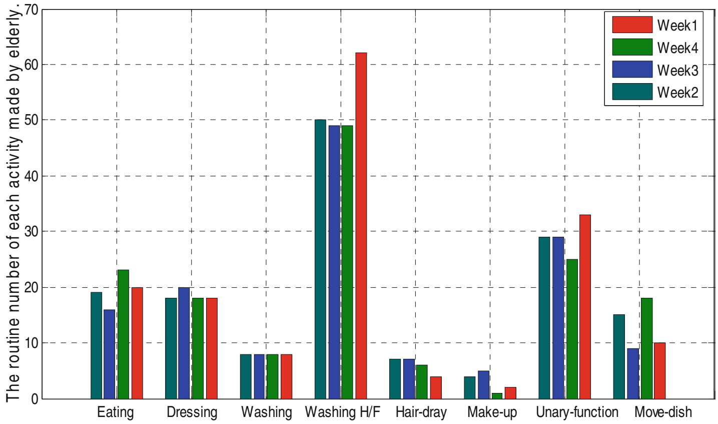

Fig. 3. The routine number of elapsed activity by week during a month.

Another crucial factor, it is very important in the abnormal activities detection that is the routine duration of each activity, so the routine duration of the activity encourage us to really know the behavior state of our elderly. Then it is necessary to study the routine duration of activities (ADL) in different period of time in the aim to having important information about our seniors behavior which will help us thereafter in our proposed algorithm.

Figure 4 shows the routine duration of some activities (Eating, Dressing, Washing Hand/Face and Unary-function) during 4 weeks in the aim of detecting almost the maximum and the minimum of the routine duration. From Fig. 4 we can deduce each minimum limit and maximum limit of the duration from each curve. For example the curve one shows the routine duration of the eating activity during 4 weeks, the same about the dressing, washing H/F, and Unary-function. The following equations show how to compute the threshold of the min/max routine duration.

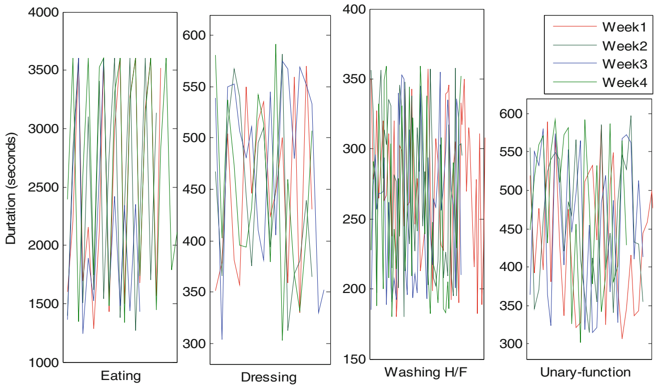

Fig. 4. The routine duration of activities (eating, dressing, washing hand/face and unary-function) in different weeks.

Max routine duration activity threshold (Max RDA):

$$\frac{\sum_{i=1}^{n} min(durtion\ activity)}{n} + logical\ adjustment \tag{2}$$

Min routine duration activity threshold (Min RDA):

$$\frac{\sum_{i=1}^{n} max(durtion\ activity)}{n} - logical\ adjustment \tag{3}$$

The logical adjustment is a parameter responsible to determinate the min and max duration thresholds, It is fixed according to the state of the person (health state, age, behavior, etc.).

4.2 Concepts of the Unusual Behavior Algorithm

The goal of our proposed algorithm untitled "Unusual Behavior Algorithm (UBA)" is to protects and monitors the life of elderly people. Firstly, our algorithm takes into consideration any unusual activity based on the min/max routine duration during a week, so each detection of unusual duration of activity is saved. Then for each week we control the result of the unusual duration number. Secondly, we can evaluate that our person has a normal state or a behavioral disturbance from the unusual duration number. For this purpose, we must propose a parameter that allows us to fix the state of the person, so the unusual duration threshold number is defined depending on the person's behavior. In the following we present the pseudo code of our algorithm.

Pseudo code of UBA:

```
Var
  Duration activity (DA) = End time activity-Start time activity;
  Unusual Duration Activity Number = UDAN;
  Unusual Duration Threshold Number = UDTN;
  While time< 604800 (week duration/sec)
      Switch (ADL){
         Case{Actvity(n) }
          If  DA(n) < MinRDA || DA(n)> MaxRDA
                   UDAN(n)= UDAN(n)+1;
           End
       End
  End
  if time= 604800 (week duration/sec)
        If UDAN (n)> UDTN
          unusual activity state =1
        else
          unusual activity state =0
  End
  End
```

5 Implementation and Results

To evaluate the performance of the RO-NN based on GA, we must calculate the prediction error. The error function indicates how the prediction of our network is close to the target values and, therefore, what adjustment should be applied to the weight and bias in the learning algorithm in each iteration. Therefore, we evaluate *the root mean square error* (RMSE) given by:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_i - X_i)^2} \tag{4}$$

Where, N is the number of learning observations, Y_i represents the predicted data (network output), and X_i represents the real data (network input) of the ith observation.

In order to have a better result, we determine at the beginning the best structure of our model (input, output and hidden neuron number). Firstly, we study the impact of the hidden and output neuron number on the certainty rate and execution time to select a better structure. Table 2 shows the different structure of the RO-NN-GA and their impact on the RMSE and the learning elapsed time.

Table 2. Comparison of the structure (number of hidden and output neuron) of the RO-NN-GA model in terms of the error and the elapsed learning time.

Number of hidden and output neuron of the RO-NN-GA				
	Hidden neuron 16 Output neuron 8	Hidden neuron 10 Output neuron 4	Hidden neuron 8 Output neuron 4	Hidden neuron 6 Output neuron 4
RMSE	0.00250	0.00155	0.00100	0.0009
Elapsed learning time (seconds)	3025,2098	2971,2806	2803,5581	2690,7309

So, from Table 2 we notice that the RO-NN based on GA has a good result from the structure that comprise a 6 hidden neuron in the hidden layer and 4 output neuron about the output layer in terms of the RMSE and the elapsed learning time. Consequently, we execute the results of the RO-NN based on GA using one input neuron, 4 output neuron and 6 hidden neurons, during a month. To confirm the performance of the model we must compare the RMSE obtained by RO-NN based on the GA with the NARX model based on multi-layer back-propagation algorithm and the Elman model based on multi-layer back-propagation algorithm Table 3 summarizes all results showing better performance of our proposition.

Table 3. The RMSE of the predicted results of the RO-NN-GA model, NARX based on multi-layer back-propagation algorithm, and Elman based on multi-layer back-propagation algorithm.

Model	NARX based on multi-layer back-propagation algorithm	Elman based on multi-layer back-propagation algorithm	RO-NN-GA
RMSE	0.0517	2.7800	0.0009

Then we can conclude that the RO-NN based on GA is more efficient and precise than the other model since it is a stochastic algorithm. So, we notice that the concept of the recurrence and the use of the genetic algorithm in the learning step increase the certainty of the model furthermore. We can conclude that we can detect the unusual behavior of the elderly with a great accuracy. When the neural network is trained, it is necessary to go to the validation step to see the performance of our model and assess the error rate, for this reason we must evaluate our prediction results. We compare the predicted data with the real data. Figure 5 shows the actual and the predicted activities of the person according to the time.

Figure 5 shows the similarity of the predicted duration curve and the real one which shows the accuracy of our model throughout the time. So, we can say that the RO-NN based on GA can predict the usual behavior which helps us to detect any behavior change with a great certainty rate using UBA from the predicted duration.

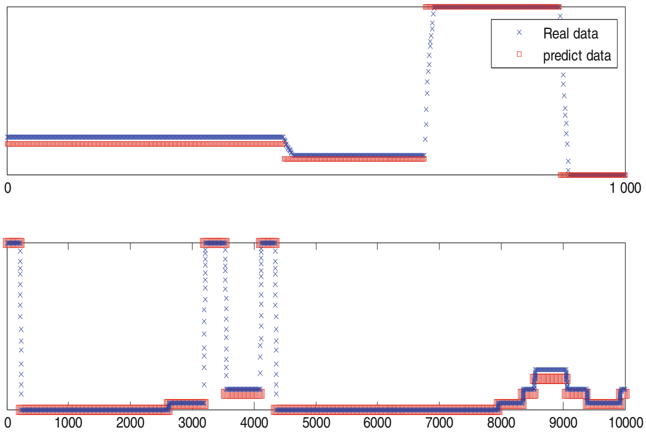

Fig. 5. The results of the prediction data predicted with RO-NN-GA compared with the real data in different interval time.

6 Conclusions

The efficient monitoring of activities of daily living regarding monitored persons in smart homes and the detection of the unusual scenarios represent on of the important issues that have been studied in the recent years. The identification of any unusual behavior or situation is very critic. In this paper, we proposed a prediction unusual behavior algorithm (UBA). The UBA is based on the routine of daily activities, the routine duration of activities and the number of routine of elapsed activity. From the UBA we can effectively identify the unusual activities, then, evaluate the behavior state of our elderly. Subsequently in this work, a recurrent output neural network RO-NN was proposed based on a genetic algorithm (GA) during the learning step. The objective was to increase the certainty of the prediction. The provided results based on the RMSE confirm that our proposed model RO-NN based on GA gives better results if compared to other models proposed previously in the literature. So we can conclude that RO-NN-GA and UBA can help the supervisor to monitor the elderly and timely intervene in the emergency perturbation state with a great confidence.

Acknowledgments. The authors would like to thank all teams of the project "e-health monitoring open data project".

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