Activity Recognition in Adaptive Assistive Systems Using Artificial Neural Networks

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***Abstract*—Our research was oriented to develop technologies for independent daily life assistance of elderly or sick persons and to improve the quality of human life. We designed a complex assistive system that can learn and adapt due to the uses of artificial neural networks (ANN). This paper presents the system developed for human activity and health parameters monitoring (temperature, heart rate, acceleration) and focuses on studies and results obtained on arm posture recognition, body posture recognition and usual activities recognition like: lying on various sides, sitting, standing, walking, running, descending or climbing stairs etc. For pattern recognition from the possible biologically inspired algorithms we opted for the ANNs. One direction of research was the design and test of several Matlab ANN models in order to find the best performing architecture. Another research direction was related to the necessary preprocessing of raw data aiming to have a better recognition rate. We find that standard deviation could be used with very good results as a supplementary input data for neurons. We optimized the number of sensors and their placement in order to obtain the best trade-off between recognition rate and the complexity of the recognition system.**

***Index Terms*—Activity recognition, adaptive systems, artificial neural networks, assisted living, e-health, patient monitoring, pattern recognition, wearable computers.**

I. INTRODUCTION

The world's population is aging and this trend increases the costs of social care and hospitalization. To reduce these costs is desirable to ensure the conditions for the elderly to remain in their preferred familiar environment. For this to be possible, intensive researches are made worldwide to ensure continuous monitoring of the health and activity performed by elderly at home and to detect in early stages abnormal situation [1]–[6]. Our research is part of this trend, to develop technologies for independent daily life assistance of elderly or sick persons and to improve the quality of human life using Internet of things (IoT) techniques [7]. This is complex assistive system that can learn and adapt due to the uses of neural networks. These R&D activity includes several topics:

1. A smart and assistive environment that allows environmental parameters monitoring and control, and related to this, indoor localization using the wireless sensor network and Wi-Fi infrastructure;
2. Design and test of a human activity and health parameters monitoring device;
3. Human activity and health status recognition using artificial neural network modelled in Matlab. Related to the artificial neural network simulations we have developed our feed forward ANN simulator [8];
4. Development of a real time activity recognition system;
5. An assistive/telepresence robot, together with assistive Android applications.

For activity and health state recognition we have developed several modules for vital parameters monitoring (temperature, heart rate, acceleration) [9], [10].

The acquired data is used to train a neural network that allows recognition of the activity or the health status of the patient and trigger alert signals in case of unusual state detection. We designed and simulated in Matlab the recognition systems for arm posture, body postures and simple activities, like standing, sitting, walking, running, *etc*. The recognition rate of the body postures was over 99 % on the data sets used for training [10]. We used the FFT transform to determine the stepping rate in walking and running activities as the most dominating frequency in the spectrum of the acceleration signal [11]. We also implemented and tested a real time recognition system using Raspberry Pi mini-computer [12].

II. HUMAN ACTIVITY AND HEALTH PARAMETERS MONITORING SYSTEM

We started the development of the prototypes using off the shelf modules in combination with modules developed by us. In the beginning we used the Chronos watch from Texas Instruments (TI) as acceleration data source combined with a chest belt from BM Innovations as heart rate data source. The receiver were built-up from a ChipKit Max32, a Wi-Fi shield and a communication shield that holds the BM receiver and the TI access point.

The assemble implements three different wireless protocols: SimpliciTI for communication between Chronos watch and its access point, BlueRobin for communication

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with the heart rate belt and WI-FI for communication with the gateway unit.

Fig. 1. Activity/health monitoring system.

A newer version of the communication shield that was developed could receive acceleration data from 2 or three Chronos watches, a heart rate monitor chest belt and has an incorporated Bluetooth module (Fig. 1.). Also the shield holds an SD card interface for storing the received data and a RTC module for time stamping the received data (Fig. 2.).

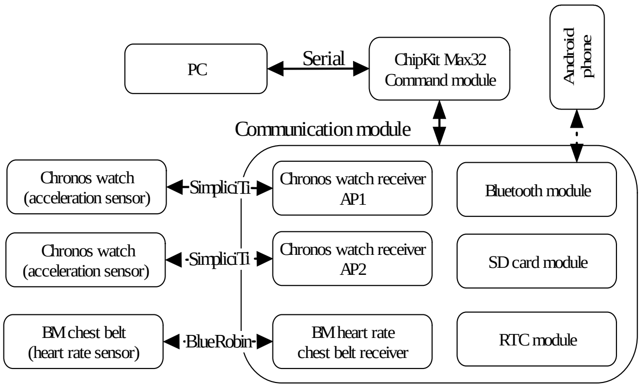
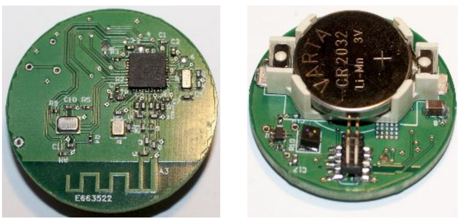


Fig. 2. Activity monitoring system.

Latter we also designed a wearable watch sized, low consumption, acceleration sensor tag (Fig. 3.). It sends the 3 axis acceleration data of the body part on which is placed. The device is composed by an ADXL350 acceleration sensor from Analog Devices, a CC2541 low power SoC for Bluetooth low energy (BLE) applications, from Texas Instruments and a TPS61220 Step-Up (Boost) converter. The tag is powered by a single coin cell battery (CR2032).



(a) (b)

Fig. 3. Acceleration sensor tag.

We made experiments related with the optimal number of sensors required and their optimal placement.

III. Human Activity and Health Status Recognition

Our research related to activity recognition were conducted in parallel in several directions. One of the direction was the development of a Matlab model of activity recognition system that use artificial neural network in order to recognize activity or health status of the patient and trigger alert signals in case of unusual state detection. Another direction was the development of hardware implemented real-time recognition system. Data provided by data acquisition system were used, on the one hand to train the artificial neural network and on the other hand to recognize the activities or health status. We modelled in Matlab several recognition systems for arm posture, body postures and for usual activities, like: lying on various sides, sitting, standing, walking, running, descending or climbing stairs, *etc*.

The recognition system should use an algorithm that is capable to learn, generalize and adapt and also to tolerate the inherent errors (noise). From the possible biologically inspired algorithms we opted for the artificial neural networks. In the process of ANN design, the number of input neurons is given by the number of input data channels and the number of output neurons is given by the number of activities to be recognized. Finding a neural network model with good performance for a given application which is also easy to implement in hardware is not exactly an easy task. Only after several simulations of different ANN models we have opted for a Feed-Forward Backpropagation (FF-BP) ANN that give good results and also is relatively easy to implement in hardware using microcontrollers or FPGAs [10]–[13]. We have made many simulations in order to find the optimal number of hidden layers and number of neurons per hidden layer(s). Also we conducted studies regarding the proper activation function and best performing training function. We concluded that good results could be obtained with two-layer FF-BP network, with sigmoid activation function on both the hidden and the output layers. We have chosen Levenberg-Marquardt training method because on the one hand it is the fastest backpropagation algorithm offered by Matlab and on other hand it gives goods results. For performance evaluation we used the mean squared error (MSE) function.

A. Arm Posture Recognition

The first recognition experiments were made for 6 arm postures. Acceleration data are supplied by TI Chronos smart watch. The ANN model is presented in Fig. 4. The recognition rate was 100 % on the data used for training.

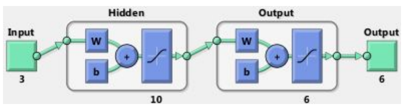


Fig. 4. ANN used for arm posture recognition.

B. Body Posture Recognition

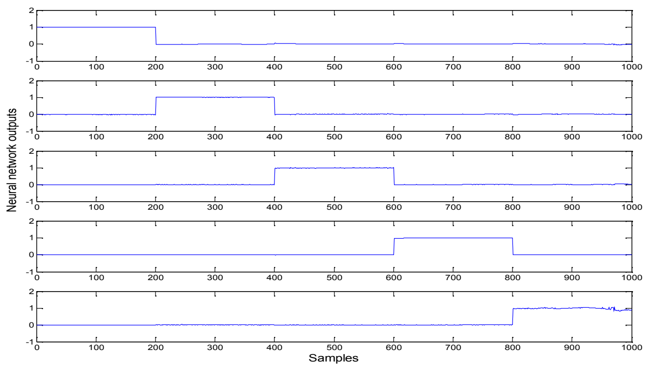


Fig. 5. ANN output for the 5 body postures.

The next step toward activity recognition was the recognition of 5 body postures. We defined the 5 postures: sitting, prone, supine, left lateral recumbent and right lateral recumbent. As acceleration data source we used the Chronos watch fixed on chest. We have modelled an ANN with 10 neurons on hidden layer and 5 neurons on the output layer. The recognition rate was 99.96 %, MSE = 3.6747e-004.

C. Activity Recognition

The main research activity was related to activity recognition and was conducted in several direction. We have established 17 common activities to be recognized (Table I).

TABLE I. ACTIVITIES TO BE RECOGNIZED.

1. Standing,	10. Left bending
2. Sitting	11. Right bending
3. Supine	12. Squats
4. Prone	13. Standing up/Sitting down
5. Left lateral recumbent	14 .Falls
6. Right lateral recumbent	15. Turns left and right
7. Walking	16. Climbing stairs
8. Running	17. Descending stairs
9. Bending forward	Transitions

Using a 27 samples/second rate we acquired 600 samples for each activity, from three acceleration sensor placed on the chest.

One direction of research was the design and test of several Matlab ANN models for activity recognition in order to find the best performing architecture, as reported in [10]. Using a two layer architecture we obtained a recognition rate above 95 %.

Another research direction was related to the necessary preprocessing of raw data aiming to have a better recognition rate. As it is presented in the literature, the data can be preprocessed to obtain new features as Mean value, Variance, Energy, Correlation coefficients, Frequency-Domain Entropy, Log FFT Frequency Bands, *etc*. [14]–[19]. After several simulations we find that the standard deviation could be used with very good results as a supplementary input data for the neurons. In the training phase of the ANN we tried to calculate the standard deviation over all the samples belonging to an activity (row 2 in Table I.) or over a window with different width (rows 3-6 in Table II.). X-Acc, Y-Acc. and Z-Acc. represent the row acceleration data while X+Y+Z-Acc. is the sum. Std_w600(X+Y+Z-Acc.) is the standard deviation over all samples belonging to one activity while Std_w50(X+Y+Z-Acc.) is the standard deviation over a window of 50 samples. The difference between rows 3-6 consist in the threshold level (0.5, 0.6, 0.7 and 0.8) for the step activation function used in the output layer. The results are shown in Fig. 6.

TABLE II. RECOGNITION RATES AS FUNCTION OF INPUTS.

	ANN input data	
1	X-Acc, Y-Acc, Z-Acc, X+Y+Z-Acc	95.44 %
2	X-Acc, Y-Acc, Z-Acc, X+Y+Z-Acc, Std_w600(X+Y+Z-Acc)	96.28 %
3	X-Acc, Y-Acc, Z-Acc, X+Y+Z-Acc, Std_w50(X+Y+Z-Acc)1	98.06 %
4	X-Acc, Y-Acc, Z-Acc, X+Y+Z-Acc, Std_w50(X+Y+Z-Acc)2	98.07 %
5	X-Acc, Y-Acc, Z-Acc, X+Y+Z-Acc, Std_w50(X+Y+Z-Acc)3	97.81 %
6	X-Acc, Y-Acc, Z-Acc, X+Y+Z-Acc, Std_w50(X+Y+Z-Acc)4	96.28 %

Another direction was conducted in order to establish the number of sensors and their optimal placement. We acquired 600 samples for each activity, from three acceleration sensors placed on different parts of the body. One is placed on the right hand (Acc1), a second one above the right knee (Acc2) and the third one on the chest (Acc3). After a few first experiments it was obvious that the third accelerometer is difficult to wear and does not significantly improve the results. This is why it wasn't used in further experiments. The results concerning recognition rates in different arrangements of sensors are summarised on Table III. 2Acc is the setup with both sensors Acc1 and Acc2. For 2Acc configuration we present results for ANNs with one hidden layer with 20, 25 and 30 neurons and for an ANN having two hidden layers with 15 and 25 neurons respectively.

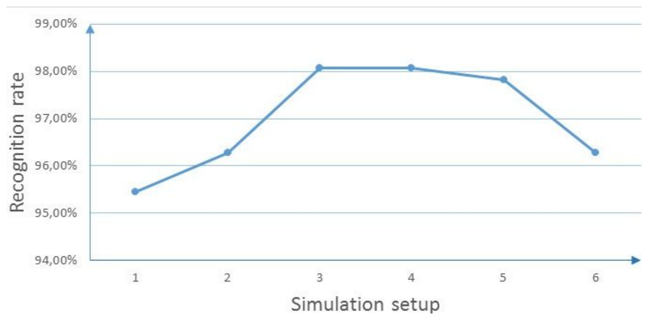


Fig. 6. Recognition rate using data from one acceleration sensor and different preprocessed input signals.

TABLE III. RECOGNITION RATES AS FUNCTION OF SENSORS ARRANGEMENTS.

	Acc1	Acc2	2ACC	2ACC	2ACC	2ACC
	20 neur.	**20 neur.**	**20 neur.**	**25 neur.**	**30 neur.**	**15 + 25 neur.**
1	99,97 %	100,00 %	100,00 %	99,98 %	99,91 %	99,98 %
2	100,00 %	99,96 %	99,93 %	100,00 %	99,99 %	99,53 %
3	99,94 %	100,00 %	100,00 %	99,52 %	99,95 %	100,00 %
4	98,99 %	99,63 %	99,47 %	99,98 %	99,76 %	99,98 %
5	99,51 %	99,69 %	99,46 %	99,32 %	99,61 %	99,88 %
6	99,51 %	100,00 %	99,46 %	99,68 %	99,64 %	99,51 %
7	95,73 %	99,14 %	99,53 %	98,02 %	99,54 %	99,41 %
8	97,73 %	99,02 %	99,51 %	99,51 %	99,51 %	99,75 %
9	97,57 %	95,29 %	94,34 %	97,25 %	99,16 %	98,39 %
10	96,83 %	95,19 %	96,61 %	98,63 %	97,62 %	98,58 %
11	94,28 %	95,35 %	98,25 %	98,35 %	97,79 %	99,09 %
12	99,01 %	97,21 %	98,61 %	98,78 %	98,32 %	99,75 %
13	97,51 %	97,48 %	97,97 %	99,00 %	98,91 %	99,93 %
14	96,41 %	96,71 %	97,30 %	96,79 %	97,57 %	97,86 %
15	97,23 %	97,61 %	98,87 %	98,59 %	98,69 %	98,81 %
16	95,77 %	98,05 %	98,61 %	99,09 %	98,88 %	99,01 %
17	98,47 %	99,09 %	98,86 %	99,09 %	99,24 %	99,16 %
All	97,91 %	98,20 %	98,63 %	98,92 %	99,06 %	99,33 %

Figure 7 shows the recognition rates of the static activities (Standing, Sitting, Supine, Prone, Left lateral recumbent, Right lateral recumbent) as a function of different sensors arrangements and the number of neurons on the hidden level of the neural network.

In Fig. 8 we can see the recognition rates for selected dynamic activities (Walking, Running, Standing up/Sitting down, Falling, Climbing stairs, Descending stairs) as a function of different sensors arrangements.

Observing the results presented in Fig. 7 and Fig. 8 it can be concluded that overall recognition rate for the static activities is better than for dynamic activities.

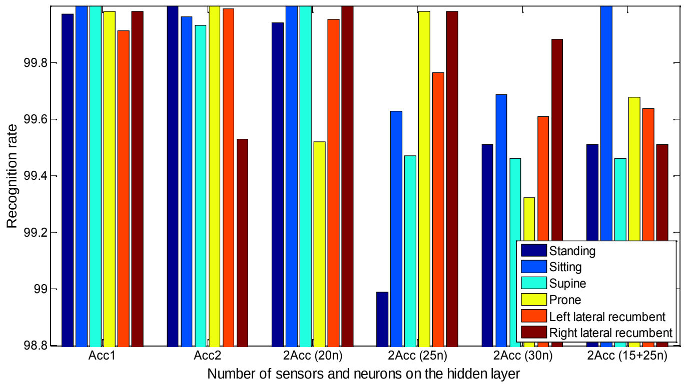


Fig. 7. Recognition rates for static activities.

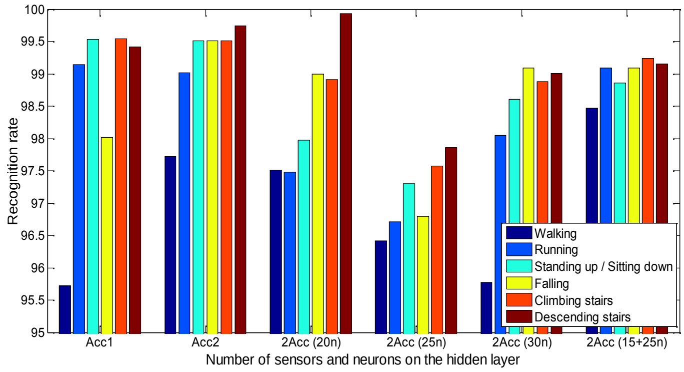


Fig. 8. Recognition rates for selected dynamic activities.

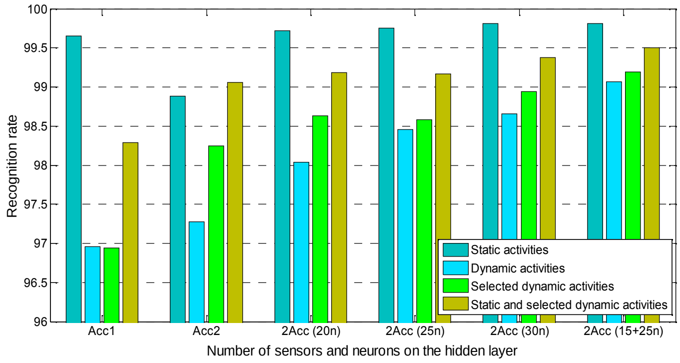


Fig. 9. Comparison between recognition rates for static and selected dynamic activities.

Analysing the results from the point of view of the sensors setup and the number of neurons of the neural network, it can be seen that for static activities the recognition rates are between 0.5 % limits for all possible combinations. For all dynamic activities the best results could be obtained using the two accelerometers setup and an ANN with 2 hidden layers. For the selected dynamic activities we obtained good results even for the one accelerometer setup (Acc2) that implies that we can use a simpler artificial neural network with one hidden layer with only 20 neurons. This setup represents the best trade-off between recognition rate and the complexity of the recognition system.

IV. CONCLUSIONS

This work presents studies made regarding recognition of usual human activities using ANNs. The recognition system is a part of a larger system developed for assisting elderly or peoples with special needs. The human activity and health parameters monitoring system was developed and optimised regarding good recognition rate using minimal resources. The use of ANN was found to be very effective even for architectures with one hidden layer with 20 neurons. It was demonstrated that even using a single 3-axis acceleration tag combined with proper signal preprocessing *e.g.*, mean, standard deviation, etc. very high recognition rates can be obtained. Comparing our results with those presented in [20]–[25] we can conclude that our method give better results. As expected the recognition rate for the static activities was better than for dynamic activities. We made also frequency domain analysis. FFT transform was used to determine the stepping rate in walking and running activities. We also implemented and tested a real time recognition system using Raspberry Pi mini-computer. Further research will be made regarding the best performing, hardware implementation friendly, ANN.

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