

FALL DETECTION USING BIOLOGICALLY INSPIRED MONITORING

Artificial Immune System in the Area of Assisted Living

Sebastian D. Bersch, Djamel Azzi and Rinat Khusainov

School of Engineering, University of Portsmouth, Portsmouth, UK

Sebastian.Bersch@port.ac.uk, Djamel.Azzi@port.ac.uk, Rinat.Khusainov@port.ac.uk

Keywords: Artificial Immune System, AIS, Fall Detection, Health Monitoring, Wellbeing, Accelerometer.

Abstract: This position paper supports the use of Artificial Immune System (AIS) in the area of Ambient Assisted Living (AAL). While AIS has been used for anomaly detection and classification in a wide range of applications, little work has been done on using AIS for detecting abnormal behaviour in health monitoring applications. In this paper, we propose to use AIS for fall detection, since falls can be seen as deviations from the normal behaviour. We justify our proposal by analysing research that has been carried out in the past using AIS in different fields and emphasising on the similarities to the area of AAL. The paper also describes the experimental setup that is currently being used for our current and future work.

1 INTRODUCTION

Due to the advances in medicine over the last half century, humans are able to live longer than ever before. Concurrently the birth rate is slowing down. These trends invert the aging pyramid (Figure 1), meaning that soon there will be more people over the age of 65 than under (Commission, Economic, & Affairs, 2009). In economical terms: fewer caretakers will have to look after more elderly people. The field of Ambient Assisted Living (AAL) aims to find solutions for this problem.

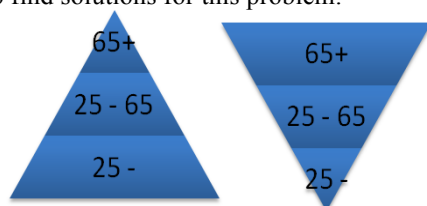


Figure 1: Aging pyramid inversion

The research directions in AAL are widely varied, but the main aim is common - to support and help the elderly to stay longer safe and healthy in their home in a cost effective manner. The work ranges from sensor development for better vital sign monitoring (Boylan, 2011) and position information to recognition of Activities of the Daily Living (ADL) (Sim, et al., 2010) over to health monitoring (Monekosso & Remagnino, 2010) (see Figure 2).

Each monitoring system will learn at one stage what “normal” health means. The problem is that the definition of “normal” is slightly different for each person and therefore introduces uncertainty in the results of each system monitoring the behaviour of an elderly person. So far researchers have concentrated on short term behaviour monitoring. These research projects included the use of Hidden Markov Model (HMM) (Monekosso & Remagnino, 2010) and Rule Based Activity Recognition (Storf, Becker, & Riedl, 2009). A new direction is to move away from the short term monitoring and consider the long term monitoring of a person (Elbert, Storf, Eisenbarth, Ünalán, & Schmitt, 2011).

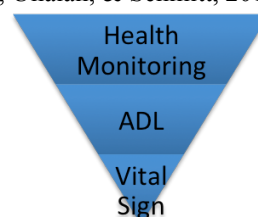


Figure 2: Range of monitoring

This long term monitoring cannot only be used for behaviour analysis but also to improve fall detection. Previously, we investigated intelligent fall detection for elderly people (ADL in Figure 2) using Fast Fourier-Transformation (Bersch, Chislett, Azzi, & Khusainov, 2011) and neural networks to successfully detect falls. This position paper makes a

case to use Artificial Immune System as a new way for adaptive long term monitoring.

2 ARTIFICIAL IMMUNE SYSTEMS AND ASSISTED LIVING

Artificial Immune Systems – AIS is a fairly new approach in Artificial Intelligence and is based on modelling the human immune system. The technique is very similar to genetic algorithms (GA) in terms of binary detectors used to match data strings with the main difference that it is better suited to detect system anomalies and abnormal behaviour patterns (Jui-Yu Wu, 2010).

For a better understanding of the AIS function, the human immune system needs to be briefly described. The general function of the immune system (IS) is to detect cells in the human body and class them using the chemical surface structure (matching) into a “non-self” and a “self” set. While the “self” set is harmless to the body and is a repetitive pattern in the body, the “non-self” set is harmful and only a sporadic pattern in the body, besides a chronic illness. This is in technical terms a system anomaly and called a pathogen in IS terms. When the human IS detects a pathogen, it has to be attacked and destroyed. This can be illustrated by looking at the different illness symptoms people have with different infections. (Timmis, 2007) (Hofmeyr, 2000).

Case for AIS in Assisted Living – In the work of (Hofmeyr, 2000), the authors point out that for AIS to be effective, an application should have the following features:

- Require pattern classification and response
- Require a distributed architecture scalable to environments with arbitrary numbers of nodes
- Address problems for which there is some commonality of patterns across the nodes, i.e., multiple nodes see the same or similar patterns within some limited time period
- Require the detection of novel anomalous patterns
- Change behaviour slowly over time
- Have storage capacities on any single node that are small compared to the amount of information required to represent all possible normal patterns

These application requirements need to be compared to the future research areas listed in the Ambient Assisted Living Roadmap of the AALANCE

(Broek, Cavallo, Odetti, & Wehrmann, 2009) to evaluate the opportunities of AIS in AAL. The key research areas are:

- Detection of emergency situations
- Activity recognition
- Handling imperfect information
- Fusing sensor data

Analysing the AAL research areas, the main qualities that are needed are data fusion and pattern recognition, which matches the ones for an effective AIS implementation.

Previous Work – AIS has been used in a wide range of research areas including fault detection and monitoring systems. The past research in AIS has mostly looked into detection of deviations from normal behaviour.

In the research work of Cai et al. (Yixin Cai, Mo-Yuen Chow, Wenbin Lu, & Lexin Li, 2010) the authors are comparing Artificial Immune Recognition Systems (AIRS) versus Artificial Neural Networks (ANN), Logistic Regression (LR), Support Vector Machines (SVM) and K-Nearest Neighbour (KNN) for their ability for fault detection. The authors used different machine learning algorithms (including AIRS) to classify real power distribution fault data from three regions in North Carolina. AIRS outperformed the other algorithm most of the time.

Polat et al. (Polat, Expert Systems with Applications, 2008) used a combination of principle component analysis (PCA) and AIRS to classify the UCI lung cancer data set. The authors were able to achieve 100% accuracy on the data set and pointed out that this accuracy is the highest among the classifier reports in the literature. The same authors also used a similar combination of AIRS with PCA in (Polat, Expert Systems with Applications, 2008) to classify EEG signals. Nearly the same accuracy was achieved. The authors point out that the most important feature of AIRS is the ability of its self-learning and therefore enable a fully automated classification.

Another application of AIS is the area of Intrusion Detection Systems (IDS). The authors of (Golovko, Komar, & Sachenko, 2010) proposed to use AIS in IDS to detect unknown intrusion attacks. Furthermore, Hofmeyr et.al (Hofmeyr, 2000) designed an architecture for an AIS and developed a network IDS called LISYS as a proof of concept. LISYS used the simulated data as a “self” set and was then confronted with seven different unknown attacks to the system. The outcome of the test was that all seven intrusive activities were detected. A low false positive rate was achieved without compromising the ability to detect intrusions.

In the field of monitoring systems Lehmann et.al (Bersini & Carneiro, 2006, pp. 335-348) used AIS to control the heating system of an intelligent home. The aim was to learn the inhabitants' behaviour and adjust the heating pattern for the house accordingly. AIS was used to act quickly on the users' special heating demands without forgetting its normal behaviour. The AIS was able to adapt and could still react to changes in the users behaviour.

Considering the long term monitoring of the wellbeing of elderly people, several comparisons can be drawn to past work in AIS. Using the circadian activity rhythms (CAR), proposed in (Virone, 2008), as the foundation of the rhythm of an elderly person it is possible to speak of a normal repetitive pattern in living conditions, which is a necessity for AIS. The probability of a health related problem with the monitored person increases, if a deviation of its "normal" pattern occurs (Monekosso & Remagnino, 2010) (Storf, Becker, & Riedl, 2009).

In the work of Franco et al. (Franco, Demongeot, Villemazet, & Vuillerme, 2010), the nycthemeral shift (change in daily routines) is used to detect dementia related diseases. This shift represents an abnormality in a recurring pattern. Parallels can be drawn to IDS. Intrusion Detection Systems based on AIS use frequent events to build a "self" set and identify attacks through the deviation from "normal" traffic pattern (compare (Golovko, Komar, & Sachenko, 2010) and (Hofmeyr, 2000)).

The research described above supports the believe of the authors that AIS will also achieve good results in the area of fall detection and in particular the feature of self-determination of AIS which should help improve the accuracy of fall detection and reduce false alarms in ubiquitous fall detectors.

3 EXPERIMENTAL SETUP

Equipment and Data Collection – The accelerometer data that will be used for the proposed research was collected in an earlier experiment. The hardware used to collect the data was an inexpensive off-the-shelf development kit. Two Texas Instruments eZ430-Chronos 868 MHz sports watches were used with an optimised firmware (customised to achieve equal time spacing between the accelerometer samples). One watch was attached to the subject's waist, the other to its wrist. The watch samples the X, Y and Z axes each $1/10^{\text{th}}$ of a second, and sends the data to a PC. Compared to other research experiments, which use higher sampling rates (up to 160 Hz) (Cagnoni, Matrella, Mordonini, Sassi, & Ascari, 2009), a sampling rate of 10 Hz can be

considered as quite low. The use of a lower sampling rate has three main benefits:

1. Lower data generation
2. Longer battery life of the wearable sensor
3. Short peak accelerations are ignored

The Data Set – The pre-recorded data collection included three different activities, walking, sitting and falling. The records of each activity were 2 minutes long and up to 10 repetitions were available. As a consequence of the research looking into long term health monitoring, this data needed to be enlarged. The different data snippets of each activity were randomly linked together to render a simulated month worth of data. The requirements on the newly created data sets were:

- Sitting had to be a continuous activity (occurring every 4 hours)
- Falling had to be a sporadic event (once every 10 days).

The longer time frame of the data set allows the AIS to be trained with different walking and sitting behaviours of one test person. This will help to build a "normal" behaviour pattern and a fall should be detected more easily because of the deviation from normal activity.

Preparation of Data and Implementation of AIS – The first implementation of the monitoring system is designed to validate the use of AIS in the field of AAL applications. The first stage should demonstrate that the particular used data set contains a normal as well as an abnormal self set. A data instance presented to the AIS contains four attributes:

1. X-Acceleration
2. Y-Acceleration
3. Z-Acceleration
4. Acceleration Average (calculated using equation (1))

$$Avg = \sqrt{(X - Val)^2 + (Y - Val)^2 + (Z - Val)^2} \quad (1)$$

In this phase, only the data set of the arm is used and no pre-processing takes place, besides a simple averaging over the last 5 data samples. Each data instances can be presented as a 32 Bit variable. Detectors are matched with the data instances using the Hamming Distance to calculate the bit difference between both instances (see Figure 3).

X Acceleration	Y Acceleration	Average Acceleration
0 1 1 0 0 1 1 1 1 1 0 1 0 0 1 0 1 0	1 1 1 0 1 1 1 0 1 0 0 1 0 1 0 1 0	1 1 1 1 0 1 1 1 0 1

Detector
0 1 1 0 1 0 1 1 1 1 1 0 1 0 0 1 0 1 1 0 0 1 1 0 1

Figure 3: Presentation of a data instance and matching

4 FUTURE WORK

The next stage is the implementation of a monitoring system based on the described AIS method. The direct outcomes are to achieve a proof of a “non-self” and “self” set in the used acceleration data set and a dynamic adaptation in immature and mature detectors. A dynamic variation in the monitoring can be achieved by mutating detectors at specific time intervals (lifespan). The mutation process can be based on different method like random generation or more advanced clonal algorithms. Therefore further research will look into the following areas:

- Possible use of data pre-processing
- Generation of detector
- Lifespan of detector
- Matching of detector and data instance
- Uncertainty after a mature detector is triggered

The authors believe that research in these areas will lead to an improved recognition in fall detection. The research outcome will be compared against the earlier results using FFT and neural networks.

ACKNOWLEDGEMENTS

This work is supported by the University of Portsmouth under the Higher Education Innovation Fund (HEIF 4) and performed by the Digital Wellbeing Research Group at the same University.

REFERENCES

- Yixin Cai, Mo-Yuen Chow, Wenbin Lu, & Lexin Li; (2010). Evaluation of distribution fault diagnosis algorithms using ROC curves. *Power and Energy Society General Meeting, 2010 IEEE*, 1 - 6.
- Virone. (2008). Monitoring activity patterns and trends of older adults. *Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE*, 2071 - 2074.
- Bersch, S., Chislett, C., Azzi, D., & Khusainov, R. (2011, Jan 1). Activity detection using frequency analysis and off-the-shelf devices: fall detection from accelerometer data. *eprints.port.ac.uk*.
- Bersini, H., & Carneiro, J. (2006). *Artificial Immune Systems: 5th International Conference, ICARIS 2006, Oeiras, Portugal, September 4-6, 2006, Proceedings (Lecture Notes in Computer Science)*.
- Boylan, G. (2011, Jan 1). EEG monitoring in the neonatal intensive care unit: A critical juncture. *Clinical neurophysiology: official journal of the ...*.
- Broek, G., Cavallo, F., Odetti, L., & Wehrmann, C. (2009, Sep 22). Ambient Assisted Living Roadmap. 1-120.
- Cagnoni, S., Matrella, G., Mordonini, M., Sassi, F., & Ascari, L. (2009). Sensor Fusion-Oriented Fall Detection for Assistive Technologies Applications. *Intelligent Systems Design and Applications, 2009. ISDA '09. Ninth International Conference on*, 673 - 678.
- Commission, E., Economic, D.-G., & Affairs, F. (2009). Ageing Report 2009.
- Elbert, D., Storf, H., Eisenbarth, M., Ünal, Ö., & Schmitt, M. (2011). An approach for detecting deviations in daily routine for long-term behavior analysis. *Workshop: Orange Alerts - Behaviour Modeling and Health of older people in their homes (AAL 2011)*. Dublin.
- Franco, C., Demongeot, J., Villemazet, C., & Vuillerme, N. (2010). Behavioral Telemonitoring of the Elderly at Home: Detection of Nycthemeral Rhythms Drifts from Location Data. *Advanced Information Networking and Applications Workshops (WAINA), 2010 IEEE 24th International Conference on*, 759 - 766.
- Golovko, V., Komar, M., & Sachenko, A. (2010). Principles of neural network artificial immune system design to detect attacks on computers. *Modern Problems of Radio Engineering, Telecommunications and Computer Science (TCSET), 2010 International Conference on*, 237 - 237.
- Hofmeyr, S. (2000, Jan 1). Architecture for an artificial immune system. *Evolutionary Computation*.
- Jui-Yu Wu; (2010). Computational Intelligence-Based Intelligent Business Intelligence System: Concept and Framework. *Computer and Network Technology (ICCNT), 2010 Second International Conference on*, 334 - 338.
- Monekosso, D., & Remagnino, P. (2010). Behavior Analysis for Assisted Living. *Automation Science and Engineering ...*.
- Polat, K. (2008, Jan 1). Artificial immune recognition system with fuzzy resource allocation mechanism classifier, principal component analysis and FFT method based new hybrid automated *Expert Systems with Applications*.
- Polat, K. (2008, Jan 1). Computer aided medical diagnosis system based on principal component analysis and artificial immune recognition system classifier algorithm. *Expert Systems with Applications*.
- Sim, K., Yap, G.-E., Phua, C., Biswas, J., Phyo Wai, A., Tolstikov, A., et al. (2010). Improving the accuracy of erroneous-plan recognition system for Activities of Daily Living. *e-Health Networking Applications and Services (Healthcom), 2010 12th IEEE International Conference on*, 28 - 35.
- Storf, H., Becker, M., & Riedl, M. (2009). Rule-based activity recognition framework: Challenges, technique and learning. *Pervasive Computing Technologies for Healthcare, 2009. PervasiveHealth 2009. 3rd International Conference on*, 1 - 7.
- Timmis, J. (2007, Jan 1). Artificial immune systems—today and tomorrow. *Natural Computing*.