Neuro-fuzzy Indirect Blood Pressure Estimation during Bruce Stress Test

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Abstract: An accurate blood pressure monitoring method during the course of an exercise stress test is paramount. This is due to the fact that the patients are under intense physical pressure, and most of the time, are usually afflicted with cardiovascular problems. Exercise or intense physical activities elevates blood pressures, which renders cuff-based measuring systems highly inaccurate, but convenient for lesser artifacts. Much research has been conducted on The Pulse Arrival Time (PAT), and it was concluded that it is inexplicably linked to blood pressure. In this study, we propose a novel approach using a neuro-fuzzy system (Fuzzy Type I) and Adaptive neuro-fuzzy inference system (ANFIS)for cuffless blood pressure estimation before, during, and after the stress test. Systolic BP and diastolic BP estimation were carried out in this study as well. There are no significant advantages in having lower error rate and/or higher correlation coefficients between the fuzzy systems. However it has been shown that the results of the non-linear fuzzy estimators possess higher correlation and lower errors than the Least Squared regression introduced in previous studies.

1 INTRODUCTION

The measurement of blood pressure are indicative of some of the mostimportant vital signs and state of health of different parts of the human body,such as the heart and kidneys. Usually, the first thing a doctor would check if a patient complains of pain in their left hands right after a physical activity or sudden dizziness that leads to a blackoutis the patient's blood pressure. The amount of force applied to the internal walls of the arteries relyon different factors,such as the heart rate, stiffness of the vessels, vessels' diameters.

An automatic non-invasive blood pressure measurement, especially during exercise stress test, is salient (Pickering, 2005). Generally, most of the systems that automatically measures blood pressure utilize the oscillometric method (Baker, 1997). However, non-invasive methods of monitoring and measuring blood pressure such as Korotkoff sounds (Pickering, 2005), or oscillometry (Baker, 1997), is regarded as inaccurate at best, due to the integration of numerous error and artefacts. Studies have proven that motion artefact constitutes one of the major problems in this context.

Many problems in cardiovascular systems may not be obvious via normal medical check-ups. Some of these problems manifests during physical activities,such asclimbing stairs, walking fast or running, or anyactivity that increases the heart rate. In these cases, the heart and other organs require an elevated volume of blood, and if any arteries are problematic, the patient will experience an intense amount of pain. In this situation, before any invasive diagnosis or medical treatment activities such as angiography is attempted, doctors will usually require patients to undergo a Medical exercise stress test.

Monitoring medical parameters of the patient plays a critical role the medical decision making process. One of the most common tests for determining medical parameters is the treadmill test, with Bruce protocol. During this test, a 12-lead ECG and blood pressure needs to be monitored in order to

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check for the occurrence of any problem in thecoronary or peripheral arteries.

Direct blood pressure measurement is almost impossible during exercise, due to body artefacts that might generate noises and disturbances to the extent that the measurement becomes inaccurate or unacceptable. It should also be noted that cuff-based measurement during exercises can be painful, due to the increase of blood pressure. The Pulse Arrival Time (PAT) measurement is capable of generating different information regarding a cardiovascular system (Poon, 2005). Exercise affects the properties of cardiovascular and blood, so the viscosity of BP (Naka, 2003), diameters of arterial and vessels (Kingwell, 1997) and the flexibility of vessels increases (Zhang, 2007). Indirect BP estimation using the PAT-approach is cuffless; disadvantages of the auscultatory and oscillometric methods will be virtually nonexistent. Furthermore, these techniquescause a lot of discomfort, pain, and restrict the mobility of the patients.

PAT is the time interval between the R-peak of an electrocardiogram (ECG), and a reference point in a pulse pressure signal in the same cardiac cycle. The R-peak is used as a reference to demonstrate the ventricular depolarization. Generally,the pressure pulse is detected by an optoelectronic set. Photo Pletysmogram (PPG) or the Pulse Oximetery are the two common names of devices used for the purpose of blood pressure pulse signal recording.

PAT is made up of two main components: the pre-ejection period (PEP) and the vascular transit time (TT). PEP is defined as the time interval from theinitial contractions in left ventricular until the blood is ejected from the heart. It is also classified asan electro-mechanical delay,while TT is the duration for blood pulse pressure to propagate via a segment of arteries. It has been tested and confirmed that PAT has higher correlations with blood pressure, rather than only TT, during and after exercises (Wong, 2011).

Artificial intelligence such as fuzzy systems and neural network (NN) is capable of providing a solution for indirect blood pressure measurement. An advantage of this method is that they perceive the system as a black box, and do not require a mathematical model for estimation. Non-linear in-out mapping, adaptivity and flexibility (Forouzanfar, 2011). (Jia-Jung, 2002) proposed a developed model of Fuzzy logic controller in a non-invasive and continuous BP in radial arteries. Classification of BP into different groups such as high, normal and low has been done in (Colak, 2003). Using a hybrid neuro-fuzzy technique, a novel method has been proposedfor blood pressure estimation by oscillometric (Forouzanfar, 2011).

The main goal of this study is to investigate the cufflessblood pressure estimations before, during,and after a medical stress test.The correlation between BP and parameters such as the Heart rate and PAT will be carried out. Our previous study indicated that Systolic BP (SBP) and Diastolic BP (DBP) estimation during the five stages of stress test is acceptable, based on least-squares regression on the data derived from 55 subjects (Colak, 2003).

In this paper, BP estimation, utilizing LS regression, is retested for 87 healthy subjects. Then, by using more intelligent methods, we are going to demonstrate the fact that the accuracy and correlation of the estimation significantly increases. This technique will greatly augment our ability to monitor BP during the medical stress test, and prevent sudden deathsduring the test.

2 METHODOLOGY

Many research groups conducted research on indirect and cuffless blood pressure measurements. The Moens-Kortwege model, experimental procedures, and dynamics of blood pressure during the exercise stress test are discussed in this section.

2.1 Corrected Moens-Kortwege Model

The Moens-Kortwege equation describes the relationship between blood pressure and Pulse Wave Velocity (PWV). A corrected version of the Moens-Kortwege equation is presented. When the heart contracts, the blood pressure wave speed is given by:

$$PWV = \frac{d}{TT} = \sqrt{(1-\sigma^2)Eh/\rho 2r} \qquad (1)$$

where E is elasticity modulus of vessel wall, h is wall thickness, ρ is density of blood and r is the vessels radius and σ is known as Poisson's ratio, which is the ratio of transverse to longitudinal strain (Shahsavari, 2011). Parameters in the equations are subject-dependent, which means that self-calibration is necessary.

The linear relationship between PAT and PAT-HR during the stress test has been investigated, and for the purpose of calibration, a new method has been proposed (Colak, 2003).

2.2 Experimental Procedure

This study was performed on 87 subjects, (52 male),

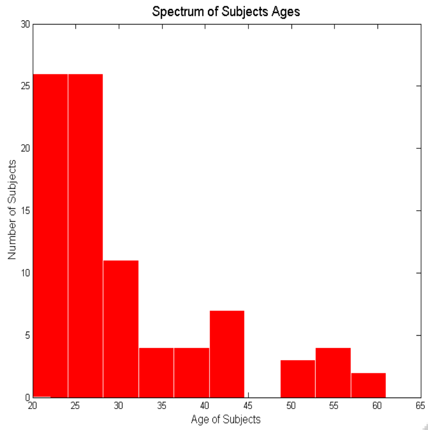

Figure 1: Spectrum of the subjects' ages participated in the experiment.

aged between 21 and 57 years (mean 31 years, SD 10). The age spectrum of the subject that participated in this experiment is illustrated in Fig.1. The subjects were healthy, 39 of them were non-smokers,and none of them had been diagnosed with any cardiovascular diseases. The standard ECG was measured with Ag/AgCl electrodes in lead II Mayson-Likar configuration (Man, 2007).

In this experiment, the ECG (lead II), Photopletysmograph signal were simultaneously collected at different stages. ECG and PPG were measured by ADInstrument acquisition system (PowerLab/8SP) at 1KHz sampling rates,while blood pressure was measured using Bionet Holter (Model:BM1), with BP modules of SUNTECH company. Stress tests were conducted using a treadmill (Model: 870A, Ram, Italy), and theblood pressure was measured on the subjects' left arm.

The protocol of the experiment consist of resting before the test, walking, running slowly, and running fast, and resting after the test. Subjects were asked not to eat (three hours)or drink (one hour)prior to the test. They were sitting for about 5-10 minutes in order to relax before the test, and their ECG, PPG, HR wascontinuously being recorded, and their BP were measured once before and after this stage. Then, the subjects are instructed to begin walking and running. The speed and the incline of the treadmill were increased in accordance with the Bruce Protocol. ECG, PPG and HR were continuously measured, while the BP wasmeasured every three minutes. Depending on the abilities and the age of the subjects, they continued with the test until one of the following signs was detected by the clinical staff:

a. $HR > (210 - Age) * 0.85$
b. Any abnormal increase or decrease in BP
c. Unusual arrhythmia in ECG
d. Dizziness, headache or nausea
e. Muscle cramps
f. Clinical staff decides not to continue the test.

Right after completing the tests, the BP is measured. The subject would then be allowed to rest. ECG, PPG and HR were still monitored during rest, due to the subjects' health. The BP was measured once after one minute of rest, and once after five minutes; this is done to establish arecovery trend. If the vital signs of the subject reverted to normal, the test is completed;however, they are still required to remain within the premises for an additional half hour for safety purposes.

2.3 Dynamics of Blood Pressure

When a subject walks on a treadmill, their HR increases, but the stiffness and diameter of the arteries remains unchanged, while the BP increases. Depending on the physiological parameters of each person, and the forces exerted by BP against the walls of the arteries, when this force reaches a threshold, the brain alters the stiffness and the diameters of the arteries, which decreases the BP. Again, by starting from walking to running, this cycle is repeated. So, in normal people, fluctuations in BP should be detected during the test.

Increasing BP without fluctuation might enable us to detect potential kidney problems. Any drastic or sudden drop in BP, provided the subject is not overweight or obese, may be indicative of vessels' rupture. This is one of the reasons that it is absolutely imperative that BP is constantly monitored during stress tests, as constant monitoring will allow us to avoid injuries during these tests.

3 SIGNAL PROCESSING

ECG and PPG are sampled at a 1 KHz frequency. Signals are filtered by a zero-phase band pass filter, with cut-off frequencies of 1- 80 Hz, and also with a notch filter of 50 Hz for removing power line effects.

3.1 Fuzzy Estimator

Previous work has shown that BP has an inherent relationship with both HR and PAT (Mottaghi, 2012). Self-calibration is required in conjunction with this method. PAT changes with time, and also differs with age and physiological parameters. For the calibration in this experiment at rest, BP is measured once at first, as a set point. Then, the estimated blood pressure from the previous stage was taken as the set point for the current stage, as shown below:

$$BP_i = (HR_i\ , PAT_i, \widehat{BP}_{i-1}) \tag{2}$$

$$\begin{cases} i \geq 2, & BP_i = f(HR_i\ , PAT_i, \widehat{BP}_{i-1}) \\ i = 1, & BP_i = f(HR_i\ , PAT_i, BP_0) \end{cases}$$

$\widehat{BP}_{i-1}$is the estimated blood pressure of the previous stage.

3.2 Fuzzy Clustering

Clustering is a tool for discovering structures or patterns in a data set, where the objects inside each cluster are similar to other members on a degree of similarity. Hard clustering systems allows each object to be a member of only one cluster,but in fuzzy clustering, each object can be a member of different clusters, with different membership degrees (Bezdek, 1987). Fuzzy C-means was used as a clustering tool in this experiment.The FCM attempts to divide any given data set and sort them into a C fuzzy clusters with respect to certain criterion.

In FCM, each point has a degree of membership to clusters. Thus, certain points on the edge of clusters have lower membership degrees compared to points that are closer to the centre of cluster. There is an overview and comparison of different fuzzy clustering algorithms in (Setnes, 2000). The algorithm tries to minimize the objective function of:

$$w_{i,j} = \frac{1}{\sum_{k=1}^{c}(\frac{\|x_i - c_j\|}{\|x_i - c_k\|})^{\frac{2}{m-1}}} \tag{3}$$

which C is the cluster centre, x data and w is the membership values. The procedure of clustering is as below:

a. Initializing W=[w_{ij}] matrix
b. At k_{th}-step: calculation the centres vectors C=[c_j] by:

$$C_j = \frac{\sum_{i=1}^{N} w_{ij}^m x_i}{\sum_{i=1}^{N} w_{ij}^m} \tag{4}$$

c. Updating W(k), W(k+1) by equation (3).
d. If $\|W(k+1) - W(k)\| < \varepsilon$ then procedure is stopped; otherwise return to step b.

This clustering was implemented on all three inputs (PAT, HR and$\widehat{BP}_{i-1}$) on each stages of training data. The number of clusters in each input is selected as five,possessing Gaussian membership functions. Fig.2 and Fig.3 illustrate this clustering output for inputs and outputs of the training data of stage 3.

3.3 Neuro - Fuzzy Systems

Fuzzy logic is widely used in controlling and estimations. The input variables in a fuzzy system are generally mapped by sets of membership functions known as Fuzzy Sets. This process is call fuzzification. Designing of a fuzzy system consists of three steps:

a. Picking the nouns or input/output variables.
b. Defining fuzzy subsets of the nouns inputs and outputs.
c. Picking the fuzzy rules by associating output to the inputs.

The last stage means that after clustering, the input-output clusters are determined. Figures 6 and 7 show the membership functions of the input-output space post fuzzy clustering.

For example, the rules generated for Fig.2 and Fig.3 are:

- If the HR is lowest (Green), Gaussian MF and PAT is the highest (Green), MF and $\widehat{BP}_{i-1}$ is medium MF (Green), while$\widehat{BP}_i$ is the centre of lowest MF (Green).
- If the HR is medium (Red), Gaussian MF and PAT is the medium (Red),MF and $\widehat{BP}_{i-1}$ is the medium MF(Red),while $\widehat{BP}_i$ is the highest MF(Red).
- If the HR is highest (Blue), Gaussian MF and PAT is the lowest MF (Blue), and $\widehat{BP}_{i-1}$ is the highest MF(Blue), which makes $\widehat{BP}_i$the medium MF(Blue).

By combining artificial neural networks and fuzzy logic, a human-like reasoning style was proposed (Setnes, 2000). This method has been used as a system identifier in different applications (Wang, 1992), (Narendra, 1990).

3.4 Adaptive Neuro-fuzzy Inference System (ANFIS)

ANFIS architecture and training methods is presented here. ANFIS is a fuzzy inference system that utilizes a hybrid learning procedure to map input-output pairs based on human knowledge (Jang, 1993). The structure of selected system is provided

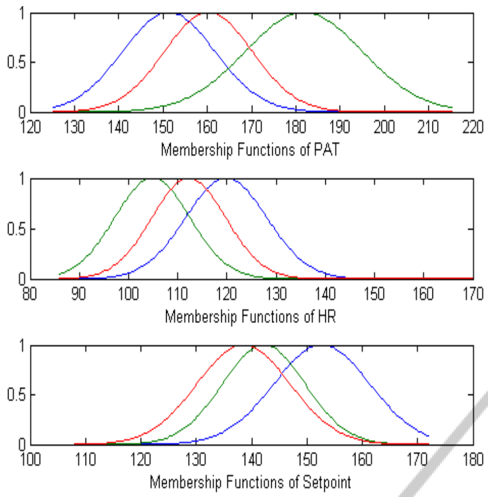

Figure 2: Membership functions of inputs after clustering.

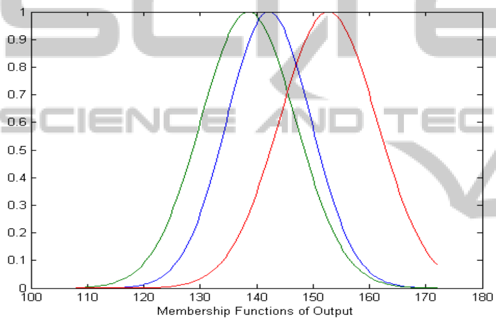

Figure 3: Membership functions of output after clustering.

in Fig.4. The membership functions were provided by the clustering part were used in this method as well.
First-order Sugeno model was used as follow:

$$f = a * HR + b * PAT + c * \widehat{BP_{\iota-1}} + d \qquad (5)$$

where HR, BP and $\widehat{BP_{\iota-1}}$ are inputs of the fuzzy system. a, b, c and d are parameters of the related inputs and f is the output of the rule.

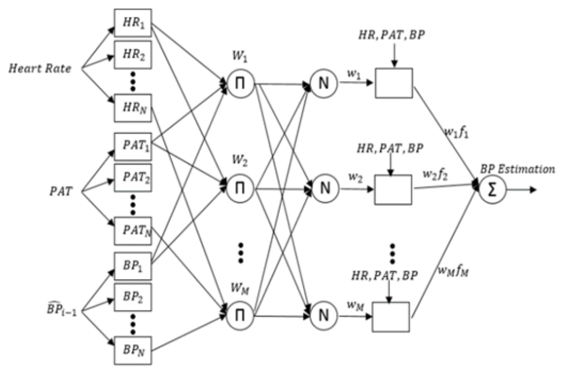

Figure 4: Architecture of Adaptive NeuroFuzzy Inference System.

Like the neuro-fuzzy method, backpropagation gradient descent has been used as backward training methods. Methods for choosing training and testing data was also similar to the neuro-fuzzy ones.

4 RESULTS

In this section, the quality of the designed system is discussed. Correlations and Errors for both SBP and DBP are shown.

4.1 Data Set

Our blood pressure data was acquired every three minutes at the end of each stage. The data set consisted of 87 subjects; 50 males and 37 females, aged 22-60. Six set of blood pressure were acquired per person during the tests, resulting in the total of 522 measurements. Measurements were at the level of the arm, done by a nurse. The ranges of the recorded data for SBP and DBP were 69-170 and 53-100 mmHg, respectively.

Table 1 comparison between the standard deviations for each stage in systolic blood pressure estimation is shown in Fig. 5. The comparison of RMSE between the neuro-fuzzy, ANFIS and LS regression is shown in Fig.6 as well.

4.2 Train and Test Strategy

Designing a fuzzy system that is capable of estimating blood pressure during the exercise stress test is quite a challenge. The system should follow the dynamics of the heart rate, arteries' stiffness, and diameter changes for it to accurately measure BP. The system should not be over-trained. Stopping the training procedure before overfitting is proposed in (Sarle, 1995), and is duly adopted in this work. The data are divided into three categories, which are the training, validation and testing of the data.

Training data should be gathered as much as possible, while validating data should encompass all points of training data.

A cross validation method has been used in this study. 77 subjects were selected randomly for training and testing, and the rest of 10 subjects used for validation. This process has been repeated 10 times and the averaged, minimum and maximum were reported.

Table 1: Comparison Between Averages of CORRELATIONS COEFFICIENTS for SBP and DBP of LS - NF - ANFIS.

Stage No.	LS		NF		ANFIS	
	SBP	DBP	SBP	DBP	SBP	DBP
Rest	0.645	0.485	0.81	0.89	0.82	0.87
stage1	0.52	0.499	0.81	0.86	0.79	0.88
stage2	0.581	0.492	0.79	0.84	0.73	0.81
stage3	0.69	0.522	0.8	0.79	0.75	0.84
Rest 1min	0.46	0.561	0.76	0.77	0.71	0.80
Rest 5min	0.72	0.41	0.71	0.78	0.76	0.80

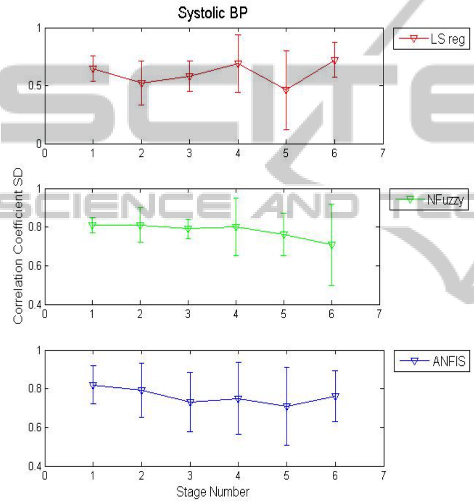

Figure 5: Mean and SD of RMSE for SBP and DBP compared between neuro-fuzzy, ANFIS systems and LS regression.

5 CONCLUSIONS

An accurate blood pressure monitoring method during the course of an exercise stress test is proposed in this paper. The system utilizes an indirect cuffless blood pressure estimation technique and using two fuzzy estimators for SBP and DBP estimation during and after exercise stress test.

Clustering the inputs-outputs pairs, and finding the membership functions and distribution of in-out sets are done by fuzzy C-means clustering algorithm. By obtaining an average coefficient higher than 0.71 and 0.77 for SBP and DBP, respectively, it is shown that not only fuzzy estimators has more potential to learn dynamics of the cardiovascular systems during and after the exercise stress test, but also they could estimate DBP at levels that are better and more reliable than previous studies.

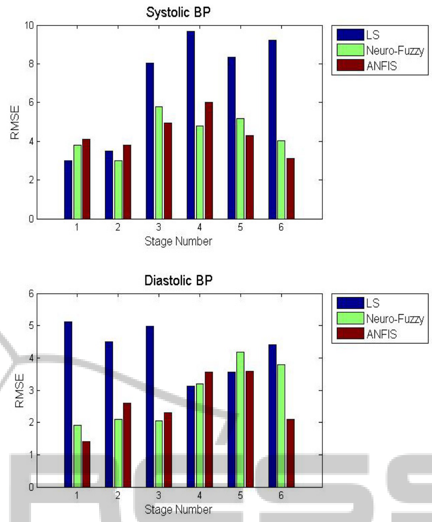

Figure 6: Mean of RMSE for SBP and DBP compared between neuro-fuzzy, ANFIS and LS regression.

The method for the calibration of the system utilized once for BP measurement before starting the test and using the estimated ones for next stages is a new method developed by this research group. It has been shown that after an average of 45 minutes, the correlation drops to lower than 0.65, and requires recalibration. This study is viable for use in studies that has higher number of subjects in different age groups, race and backgrounds to find more accurate models for each ones.

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