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Arm Movements Effects in Response to Posture Instability

Sara Manifar
Ryerson

ARM MOVEMENTS EFFECTS IN RESPONSE TO POSTURE INSTABILITY

By

Sara Manifar

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ABSTRACT

Title of Thesis:

Arm Movements effects in Response to Posture Instability

Thesis Submitted By:

Sara Manifar

Electrical and Computer Engineering Department,

Master of Applied Science Program

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In recent years, because of an increasing aging population there are higher incidences of falling according to epidemiological reports. Because of this high frequency the prevention of falls becomes a major concern. Evidence of the high occurrence and significant cost of falls on health-related quality of life, significant financial load on the health care system, and on their social impact has been provided by various epidemiological studies.

Falls are the second leading cause of traumatic brain injury (TBI), which is a major cause of death in many countries, especially the United States. Balance impairments are frequent and particularly high among people who suffer from stroke, TBI, incomplete spinal cord injuries, Parkinson's disease, multiple sclerosis and diabetic peripheral neuropathy, and in general for people who suffer from different neurological disorders. For all of these groups, balance disorders have a major social and quality of life implications, which require attention and exploration of effective ways to evaluate risk and develop training programs that prevent falls. According to the literature, the most important factors for fall prevention are suitable training programs and the availability of feasible and cost-effective comprehensive risk measurement [1, 2].

This thesis describes the acquisition of acceleration data of a human body while maintaining balance on a balance board with three-axis accelerometers. Three different algorithms of balance region detection, the wavelet transform, and the neural network were developed to segment and classify the unstable regions of the accelerometer signal. To simplify the calculation of these algorithms vector processing technique was used.

The experimental results show that arms have an effective role in the improvement of balance. From the balance region detection the duration and amount of activity can be found which will be good for prediction of falls. The wavelet transform is the best way to separate unstable periods from one another. For classification of stable and unstable parts of movements, the neural network is the best technique. It is effective to compare the amount of stable and unstable parts in more detail. The results suggest the specific role of the dominant and non-dominant arms.

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Sara Manifar

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List of Abbreviations

CoM	Body Center Of Mass
BoS	Base Of Support
CoG	The Centre Of Gravity
CoP	Centre Of Pressure
m	Metres
CNS	Central Nervous System
EMG	Electromyogram
AP	Anterior–Posterior
ML	Medial–Lateral
OLB	One Legged Stance
MAS	Motor Assessment Scale
k-NN	K-Nearest-Neighbor
FFT	Fast-Fourier Transformation
STFT	Short Time Fourier Transform
DWT	Discrete Wavelet Transform
DCT	Discrete Cosine Transform
VMU	Vector Magnitude Unit
ECG	Electrocardiography

FT	Fourier Transform
DFT	Discrete Fourier Transform
IDFT	Inverse Discrete Fourier Transform
WT	Wavelet Transformation
CWT	Continuous Wavelet Transform
MRA	Multiresolution Analysis
db2	Daubechies-2
NN	Neural Network
TF	Transfer Function
BP	Back-Propagation
LMS	Least Mean Squared
TrainLM	Levenberg-Marquardt
PSD	Power Spectral Density
MSE	Mean Squared Error

CHAPTER 1: Introduction

Recently, there has been increase in the number of falls because of population aging. As such, more research is being conducted on the factors involved in falls, avoiding obstacles and changing directions being the most common. This chapter consists of a detailed literature review, describing frequency and causes of falls and defining the basic concepts related to them.

1.1. Literature Review

With the increase of an aging population worldwide and with increased life expectancy of the elderly, the maintenance of mobility, and accordingly functional independence, is becoming more and more important. Because most falls occur during moving tasks and not static tasks, keeping balance while walking and doing other everyday activities has a great effect on quality of life [3, 4 , 5, 6, 7]. One of the key elements of the elderly's quality of life is functional independence, and the ability to maintain the upright posture without assistance [3].

More than one-third of adults over 65 falls each year and these falls are the primary reason for death and serious injuries among this population [1, 3, 4, 5, 6, 7]. This may be because of decline in the collaboration of visual, vestibular and somatosensory systems, leading to more frequent destabilization, uncertainty and falls [3]. In Finland, falling has been estimated to cause the death of more than one thousand persons annually among people over 50 years old [4]. Preventive actions could reduce the risk of falling by 20 – 40 % [8]. As another example, according to data from the US National Center for Injury Prevention and Control, the hip break is the most serious falls-related injury, with causing more than a third of a million (340,000) hospitalizations per year in the US [1]. Another study found that there was a 25% frequency of falls among persons of 55 to 64 years of age and for over 65 years of age was 31%. Also, falls cause 4% of bone breaks and in total 9% of serious injuries. The frequency among those who fell 70.5% experienced ongoing health problems. Based on these statistics, falls cause more social consequences, including an increased use of healthcare and nursing home services [1]. As such, researchers and clinicians focus more on recording the number of falls, seriousness, damage and in understanding the way the system works at any related topics [3, 7].

Health professionals within a wide variety of clinical fields frequently use "balance" as a common term. The word "balance" is often used in association with terms such as stability and postural control. Many patients, including those with neurological weakness, orthopaedic problems and vestibular disorders will be evaluated with regard to balance. Even though this term use commonly and is well known, but there is no commonly accepted definition of human balance. That is why having universally accepted definitions of terms for use within clinical practice is necessary for most proprietary tests, for documentation, for explanation of patient problems to form an evidence-based practice and to provide an optimal patient care base [3].

As an example of cause relating to a greater risk of falls, the inability to walk and talk simultaneously can be mentioned [6]. Furthermore, the postural stability is important for every movement and operation. Unpredicted outside forces or one's own chosen movement can produce disturbances of postural balance [4, 9]. Young adults have better ability to perform a postural and an experimental task in comparison with healthy older adults. This has been established as a decrease in the performance of the cognitive task and an increase in reaction time for older adults. In comparison with healthy older adults, older adults with poor balance acting less well on clinical balance tests report imbalance and the use of an outdoors support more frequently, exercise less frequently, verify poorer attention ability (high scores on the Trail-Making Test), and have lower overall cognitive functioning [1, 2, 6].

Risk for falls is associated with a variety of sensory, motor, cognitive, and psychosocial variables. The response of a system to a perturbation is called stability. In a steady-state step, many small perturbations are present, and the system's response to such perturbations is called local stability. Otherwise, when walk is externally perturbed, global stability can be evaluated by measuring the response to such a perturbation. In the case of a feedback-controlled system like the human body, this response may be divided into two phases: an initial phase, which is dependent upon the steady state of the system (as it was before the perturbation) and the system's essential mechanical properties (e.g. inertia, stiffness) during daily activities, and a second, reactive phase ('recovery'), which is mainly dependent on active control and reflexes such as a slip or trip. In reality, because these two phases may act together and have an overlap, separating the assistance of these phases from the response following a perturbation is difficult [4, 5, 6, 10]. It is unclear that the ability to have balance and ability to recover balance are managed by similar motor and sensory variables, and whether performance in one of these tasks is predictive of performance in the other. Basic differences in the neuromuscular load of the tasks, including the level of muscular effort involved, the utilization of anticipatory against reactive postural control strategies, and the utilization of information from visual, vestibular, and somatosensory systems may cause little association between postural stability during quiet stance and ability to recover balance following a postural perturbation [5].

The stiffness is often characterized by measuring postural stability during a quiet stand, while the recovery is assessed by measuring the individual's response to a sudden external force or displacement of the support surface [4]. The body has a high potential energy, which guides the prioritization of balance control during almost all motor tasks, including quiet standing. This energy gives importance to the body center of mass (CoM) comparative to its base of support (BoS) and CoM must be inside its BoS for having postural stability [4, 9].

To counter the destabilization forces of weak postural adjustments the body suddenly responds with a movement. Little is known about the properties of these postural accessories, in spite of the importance of these postural adjustments to the safe and efficient performance of movement. Movement disturbs position by imposing forces on adjoining body segments; these forces arise from the inertia and momentum of the body segment moved and from the object being moved [11].

1.1.1 Summary of Some Basic Definitions

The mentioned concepts will be defined in details in this section:

Balance

The term balance (or equilibrium) is a generic term describing the dynamics of body posture to prevent falling, and as used in mechanics, is defined as loading and acting consequential actions (forces or moments), such that state of an object will still be zero and remain at rest (Newton's First Law). The position of the CoM (the centre of gravity or CoG) and the area of the BoS of that object are important to having a good balance in a static situation. It means that the CoG is within the BoS of that object, the object is balanced. On the other hand, if the CoG is moved out of the BoS, an imbalance occurs and falling happens [7, 12].

Stability

Mechanical principles command that stability exists if the line of gravity falls within the BoS, and increases with a larger BoS, a lower CoG, or a more central CoG within the BoS. For having greater stability, having the greater displacement of the line of gravity before an object becomes unbalanced is important. Also, having greater external force before causing object unbalance, the stability becomes greater [4, 9, 12].

Postural control

Posture describes the orientation of anybody segment relative to the gravitational vector. It is an angular measure from the vertical. Postural control is a condition to the maintenance of postures and activities. However, the control of balance has been identified to be associated with three broad classes of human activity:

1) The maintenance of a specified posture, such as sitting or standing

2) Voluntary movement, such as the movement between postures

3) The reaction to an external disturbance, such as a trip, a slip or a push.

These classifications contain the acts of maintaining, achieving or restoring the line of gravity within the BoS. Postural control can therefore be defined as the act of maintaining, achieving or restoring a state of balance during any posture or activity [7, 12]. The evaluation of the Postural Control System (PCS) has applications in rehabilitation, sports medicine, gait analysis, fall detection, and diagnosis of many diseases associated with a reduction in balance ability [13].

Centre of mass (CoM)

This is defined as total body mass in the global reference system (GRS) and also as the weighted average of the CoM of each body part in 3D space. The balance control system controls CoM as a passive variable.

One of the most important specifications of CoM is the COG. The COG is the vertical estimation of CoM onto the ground. Its units are metres (m) [7].

Centre of Pressure (CoP)

The point location of vertical ground reaction force vector is described as COP. It is defined as a weighted average of all the pressures over the surface of the area in contact with the ground. It is totally independent of the CoM.

For describing this, the following example can be used. If a person stands on one foot, the net CoP lies within that foot. If both feet are used by the person, the net CoP lies somewhere between the two feet, based on the relative weight taken by each foot because there are separate CoPs under each foot which is a direct reflection of the neural control of the ankle muscles. The net CoP can be found when the participants. uses the force platform. For computing and tracking the CoP changes within each foot, two force platforms must be used. Its units are metres (m) [7].

1.1.2 Timing and gain properties of postural accompaniments

Identifying patterns of postural muscle activity for different movement tasks has been focused during voluntary movement by most research on postural control. For understanding how the central nervous system (CNS) uses advanced postural adjustments to optimally control an upright stand, timing and gain of the postural control system are also important properties to examine. The timing and gain of postural accessories must be matched to the magnitude of destabilizing forces caused by the movement. Postural adjustments that arrive too early or too late can be destabilizing in themselves (i.e they will fail to match the destabilizing forces of movement). Therefore, to specify the right direction, timing and gain of postural adjustments associated with movement, the CNS requires information about the movement task and internal knowledge about the interaction between body parts (posture and movement). The stabilizing forces of postural adjustments act over a longer period with increasing interval between early postural and central responses, and also growing the gain of the postural response will increase the magnitude of stabilizing forces. For producing more optimal stabilization of posture, both timing and gain can be scaled together; but, this is not always the case. Symmetry of movement affects the timing of postural and focal responses. It is observed that the latency between postural and focal responses was longer when subjects rapidly raised a single arm versus both arms, respectively [11].

1.2. Arm movements effect for human balance

In reaching or grabbing for external supports or for supporting of impact in preparation of a possible fall, the arms may provide a protective function. Alternatively, the mechanics of the body can serve as arm movements, such as counterweight to shift the body CoM away from the direction of the fall or by generating a reactive torque to work against the whole-body sharp force or, a functional role in balance recovery after tripping [14]. Particularly, both reactive forces and changes in body joint configurations can change the straight posture by raising the arm [9]. As a classical approach to examining the harmonization between posture and movement, balance processes analysis related to arm movements can be mentioned [9, 15].

Most activities that we perform with our hands involve contact with the environment. Many tasks performed with tools are naturally unstable and therefore need additional skills, get rid of different initial conditions, neuromotor noise or any small external perturbation in unstable tasks which can lead to unpredictable and unsuccessful performance [16]. It has classically been understood that upper limb movements, represent an internal source of disturbance to balance, and for this reason, trunk displacements are paid attention to a preventive or reactive manner. In accordance with this concept, in which the postural component compensates for difficulty forced on the body by upper arm motion, one can predict that during whole body pointing movements perturbations made by arm disturbance will be cancelled out in order to reach the target regardless of stability constraints produced by the task [15, 16]. However, humans have excellent ability to control objects. This means that the CNS is able to adjust to different task dynamics. For example, one may have difficulty in opening a door for the first time due to unknown resistance. However, after one or two trials the correct force will be used, and one will open the door without difficulty and even without thinking about it [16]. By reaching for targets with the standing position, the CNS has to specify the characteristics of the arm movement by keeping the whole body CoM within the supporting base (the feet) [15].

During normal walking, the arms can get considerable pointed energy around the vertical axis through the body center [10, 14]. For instance, walking without arm swing increases the metabolic cost of walking, for two reasons: 1) the greater pointed energy relating to the vertical axis needs to be neutralized, 2) larger vertical movements of the CoM that happen when the arms do not swing upward when the trunk moves downward [10]. As an example, by adding arms to the passive dynamic walking model, which may not be realistic, the local stability of steady-state walk cannot increase. This model defines electromyogram (EMG) activity in the shoulder muscles during human walking. Another (physical) model of bipedal walking showed that in side-to- side motion when the body is moving forward, global stability decreased with the arms swinging inward, however, in contrast, global stability increased when the arms waved outward. With these findings, it can be said that global gait stability may be at least influenced by arm movement.

The sharp force of the arms at the time of tripping is harmful for recovery foot position [10]. By comparing the arm swing to normal walking, it can be seen that in tripping, less angular momentum is transferred to the trunk and legs and the momentum remains on the tripped side after trip beginning. Therefore, the trunk and legs could rotate further towards the non-tripped side; the axis result improves the length of the recovery step in the sagittal plane which needs to be as large as possible to better assist in recovery. Thus the arm movements supply more sufficient body orientation after a trip, generally for assisting a more favorable orientation of the trunk and legs for the recovery foot landing. The poor effect of transferring the primary arm momentum in the transverse plane postpones the trunk’s reaction. Postponing a transfer of the primary sharp arm momentum at beginning of trip is the most important factor of the part of arm movements for having a successful recovery from a trip [10, 14].

Despite detailed descriptions of arm movements and muscle activation, the function of these arm movements remains unclear. Irrespective of changes in the whole-body sharp force, arm height increases the time of inactivity of the body, which slows down the sharp speed of the whole body [14]. Increased inactivity may reduce performance in the primary phase of global step stability when walking with a normal arm swing. When the hands are fixed to the body, the upper body has a greater effective inactivity, and it is more challenging for perturbations to occur. The challenge may be explained experimentally by having subjects walk with restricted arm swing with their arms fixed away from the body, while rotational inactivity is further increased. Another explanation would be different trunk muscle activation model can be caused by restricting arm swing. When a fall occurs to the restricted upper body, the restricted upper body will behave more like an inverted pendulum than the free upper body, and will be less able to recover from a fall [10].

Having constraint functions can help to create optimization approaches for the predicted arm raising motion patterns' solution. Balance constraints can only be related to the anterior–posterior (AP) displacement of the CoP with dynamical parameters for the system in this optimization procedure. Based on these facts, it is more believable that the system controls the CoP instead of the CoM: first, a system's reaction to movements involving the whole-body CoM is reflected by CoP's changes; produced forces for returning to a balance position is described by the CoP. Second, the distance between the CoM's projection and the CoP is increased by changes in body position associated with arm rising; this makes the subject essentially less stable and forcing the CoM to return to a stable position within the support area by muscular actions. It follows that this active postural control will be reached by controlling a variable other than the CoM and the system will preferably choose the CoP. Finally, because pressure receptors are located under the feet, the CoP position information can be directly available to the system. In comparison, it is more difficult for the system to have knowledge about CoM positions because, the CoM is global, and it means it is a whole-body parameter, getting information about this parameter may need complex calculation. Therefore, the idea that the body's CoM position is the reference value and it is the variable controlled by the CNS is challenged [9].

Evaluating the impedance in movements which are related to a given stable or unstable interface is possible. Mechanical impedance of the human arm can be estimated from the restoring force to minor perturbations force in static positions or during movement. However, this requires many movements, and it would be more useful to have a solid model to describe the force and impedance in every dynamic relation. Impedance was shown to depend on position, force and instability but no complete model has been projected so far [16].

1.3. Strategies of postural control

There are different kinds of postural control strategies:

1) Reactive (Compensatory): involves a movement or muscular response following an unpredicted disturbance.

2) Predictive (Anticipatory): involves a voluntary movement, or increase in muscle activity, in anticipation of a predicted disturbance;

3) Combination of both: These responses may be 'fixed-support', involves the moving of the line of gravity, the BoS remains unchanged, or 'change-in support', where with moving of the BoS, the line of gravity crosses it. Some examples of fixed-support strategies are as follows: swaying from the ankle or hip ('ankle strategy' or 'hip strategy'), but grasping with a hand or stepping ('stepping strategy') is assumed as common change-in-support strategies.

Although postural control strategies have traditionally been considered reflex-like responses caused automatically by a sensory motivation, it is now considered that postural responses to maintain balance are dependent on the assessment and control of many variables by the CNS [12].

1.4. Clinical Balance Tests

Identification of subjects at high risk of regular falls and of their poor consequences must be applied for knowing the efficiency and cost-effectiveness of fall-prevention strategies. Here are some of these experiments:

- The Romberg stance [3, 17] evaluates the stability of a patient standing with his/her feet together, eyes open and hands by the sides and/or the subject closes their eyes while the examiner observes the subject for a full minute.
- Beauchet et al and Horak et al [4, 18] described one legged stance (OLB). In this test, the examiner asks the patient to stand unassisted on one leg for a period of time (e.g.30 sec) once with eyes open and once with eyes closed. The Disability to stand on one leg for 5 seconds is defined as weak OLBF and identified as a predictor of injurious falls in community-dwelling older adults.
- The Rivermead Stroke Assessment [19] tests the ability of a patient to sit unsupported (i.e. maintain a posture).
- The Motor Assessment Scale (MAS) was used in [20, 21] to test the ability of a sitting patient to perform a voluntary movement (i.e restore a posture following a predictable disturbance) and to move from sitting to standing (i.e. achieve a new posture)
- While Horak et al and Sandin and Smith [18, 22] described a test that requires a sitting and/or walking patient to respond to a lateral push to the trunk (i.e. restore a posture following an unpredicted disturbance).

while each of these clinical tests is valid assessments of a patient's balance, each test is evaluating a different aspect of postural control.

1.5. Recovery in Balance Assessment

For understanding balance recovery after a walk perturbation, many studies have looked into responses to slips and trips. For preventing a fall, for example tripping over an obstacle, the body generally makes a forward rotation during walking with perturbation of the swinging limb. For breaking a forward sharp force, the recovery foot can be placed forward as far as possible or the support limb can be used for moving forward. Strong arm movements have been experienced after perturbations of walking and of upright standing.

Understanding the role of the arms in balance recovery requires knowledge of sharp force, sharp speed and sharp direction [14].

1.6. Thesis Outline

In this study, a set of accelerometer-based tests of dynamic postural balance, and the roles of arm movements for its maintenance during balancing tasks are described.

The second chapter explains the methodology for the design and development of the instrumented balance assessment for the new balance test used in this study. This chapter describes the study's instruments, data acquisition, signal processing and statistical data analysis.

The methods and algorithms used through this study are presented in Chapter Three. The procedures include signal pre-processing, and digital signal processing methods such as the balance region detection algorithm, the wavelet transform, and the neural network. The procedures are discussed in relation to the experimental techniques.

A discussion of the results and the relevance of this study for balance diagnostics and assessment is presented in Chapter Four. The results and discussions based on the experiments from combination of custom made Matlab file and Matlab toolbox include: signal pre-processing, unstable regions detection algorithms, feature extraction and neural network classification results.

The fifth chapter contains conclusions and also suggests of the direction of future works such as the improvement of the experiment.

Chapter 2: General Methods

This chapter presents the methods used in this thesis to handle the stability and human balance behaviour. Firstly, equipment and subjects are introduced. It is important to know that the data acquisition part was done before in 2008 as a Master of Applied Science thesis by Matija Milosovic [1]. However, it is supposed to explain this useful information in more details to understand better the procedure. In this thesis the collected data were used for defining the segmentation algorithms. Secondly, some algorithms for segmentation are embodied in terms of finding stable and unstable regions.

2.1. Materials

2.1.1. Accelerometers

An accelerometer is an electromechanical device consisting of damped mass-spring systems that will measure acceleration forces based on piezo-electric properties [2, 23, 24]. There are two different kinds of forces, static or dynamic. The constant force of gravity is an example for the static force, and vibration or moving of accelerometer is an example for dynamic force. Accelerometers measure these forces and then convert them into data through X, Y and Z axes [23, 25]. Accelerometers are increasingly found in devices which are capable of supporting remote care delivery or mobile phones [26].

Some clinical applications of accelerometers are [2, 27]:

- Gait
- Balance evaluations and postural sway
- Fall risk assessment (especially detection of)
- Mobility monitoring and classification
- Metabolic energy expenditure (which is the standard reference for the measurement of physical activities)
- Physical activity (defining and comparing a group of subjects with different activity levels)
- Sit-to-stand transfers (which is an important indicator for postural instability)

In the 1950s, the first accelerometer was used for measuring human movement and had many practical concerns such as excessive, weight and its impact on the motion of the subject.

They were also very expensive and unreliable [2]. In time reliable and cheap low power accelerometer devices were developed for air-bag release systems [24, 28].

For data acquisition, accelerometers with a ±2.0g force range, a sensitivity of 1V/g for the supply voltage V_{dd}=5V and with the 0g offset set at $V_{dd}/2$ were used. These accelerometers are made by Kionix Inc. and the model is KXM52-1050. For getting correct displacements related to the arm frequencies and balance board movement, the signals were filtered. The sensors were fixed in the gloves on both arms as well as on the balance board [1, 29].

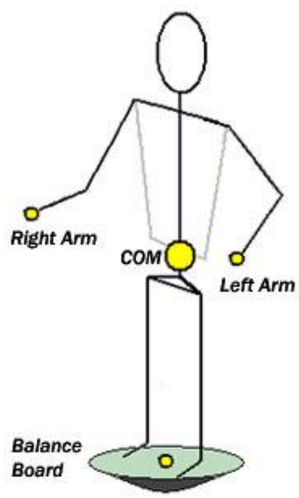


Figure 1. Sensor placement for the Balance Board test (position of accelerometers is indicated by small circles) [1]

2.1.2. Subjects

For the quantitative balance board test, four healthy volunteer participants were examined. All of the participants were right handed, healthy middle-aged adults and with a mean age of 56. The condition for participating was that the subject should have no history of neurological or other underlying disease, fear of falls, or any other diseases or injuries that affect balance [1].

2.1.3. Protocol

An experiment was conducted several times using constant conditions. The test used dynamic balance board twice: for limited and free arm movements. In the first trial, the participants were asked to keep their arms close to the body (limited arms), while in the second trial, the participants were allowed to use their arms freely (free arms). At the beginning, the test was revealed to the participants. Then, they could work approximately 15 minutes with the balance board to familiarize and get experience with it and the test. The test took approximately 30 minutes, and the examiner was always present to help the participant in emergency conditions. The participants had permission to end the test whenever they felt uncomfortable [1].

The ethics used to design the study were based on Ryerson University's Research Ethics Board procedures (REB 2009-042) to signify a minimal safety risk, and ensure the participants' confidentiality [1].

2.1.4. Balance Board Test:

The balance board tool was used for judging the participant's balance by keeping balance on a modified clinical balance tool for physiotherapy and rehabilitation [1, 13]. The balance board tests evaluate balance in three different directions: all direction (CBB), ML and AP balance separately. In this study, only CBB was evaluated. Participants attempted to maintain their balance on the balance board for one minute, and then the recorded data was used for post-processing. As mentioned before, task of balancing was assessed under limited and free arms conditions, and dynamics of the arms and balance board were recorded for both conditions. By exercising on balance board, postural balance and muscle strength can improve, especially for the elderly [1, 30].

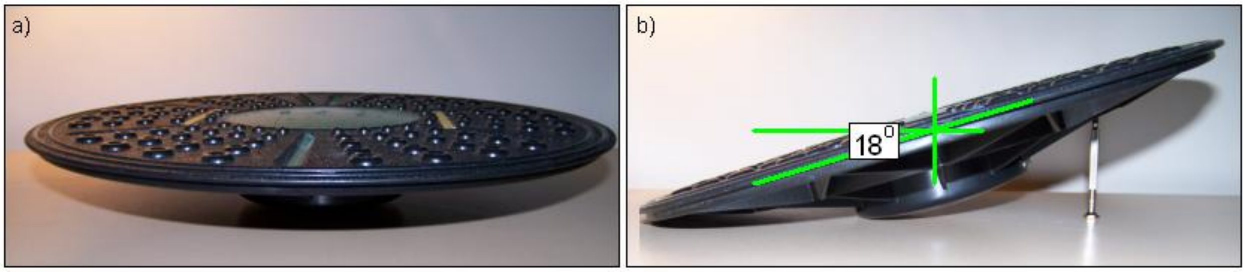


Figure 2. Shows the balance board used in the CBB balance board test. The balance board can move in all directions; a) CBB test balance board; b) CBB balance board maximal range of motion [1].

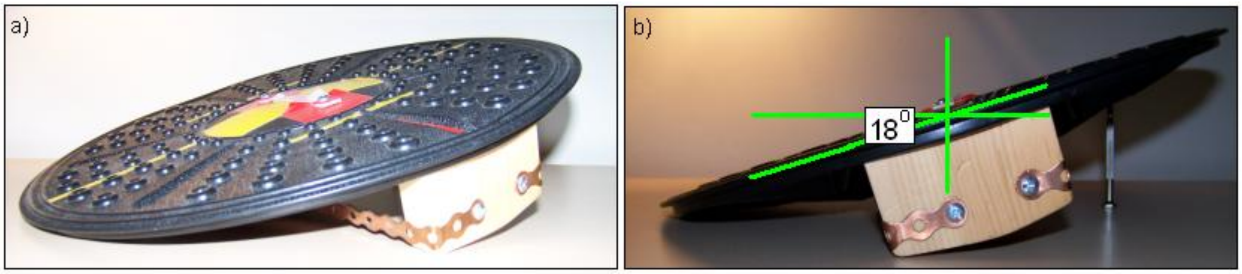


Figure 3. Shows the balance board moved in the AP and ML direction. The balance board can move only in the selected direction and is constrained in other directions; a) AP and ML test balance board; b) AP and ML balance board maximal range of motion [1].

Operation of balance board

An individual stands on an unstable surface and tries to maintain balance by not allowing the apparatus to come into contact with the ground. The individual on the balance apparatus is never in true static balance but appears to be in one of two states based on tilt dynamics measurements from the balance board. The first state or the stable state is characterized by many tiny incremental movements of a short duration, whereby the arms stay in relatively the same position and the individual body moves in order to compensate for the movement of balance board. The second or unstable state is characterized by large displacements involving random arm movements, weight shifting from one leg to another, with the individual moving back and forth. By placing an accelerometer on the balance apparatus, one can record relevant accelerations [1, 2].

Figure 4. Individual on a balance apparatus [2]

2.2. Accelerometer Segmentation Algorithms

As mentioned before, fall and seizure detection are two common applications of accelerometer signal segmentation algorithms. But, the main problem of detecting a fall is distinguishing a true falling event from normal activities such as walking fast, and sitting down [2, 23]. One common element of the method is averaging the signal, then using a threshold value to determine the segmentation periods of the signal [31]. Some algorithms supplement the classification by using logic operations [32]. Others use the root-sum-of-squares of the three signals from each tri-axial accelerometer after using low-pass filter [24, 33]. Bernmark and Wiktorin [34] used an accelerometer to evaluate arm movements and posture measurements by evaluating degree of the arm [34]. One method to understand the activity of balance control was collecting muscle activity signals and performing an analysis on those signals during standing balance from accelerometer data by low-pass filter and moving average filter, and then using two classification networks, the neural network and k-Nearest-Neighbor (k-NN) based on statistical features that extracted from each EMG signal [13]. Milosovic [1] also used the adaptive Pan and Tompkins algorithm for signal analysis. First he used the 10-point moving average filter to emphasize the balance lost, then used this model for getting derivative of the signal, and finally developed an envelope from the derivative to understand the main activity of the movements [1].

Prieto et al [35] calculated four measures of postural steadiness from the CoP data in each of the anterior-posterior (AP) and medial–lateral (ML) directions. In all trials, a force plate (model 6090H, Bertec, Worthington, OH) was used to measure (at 540 Hz) the position of the CoP between the feet and the ground. The CoP time series were then filtered using a recursive fourth order Butterworth low pass filter with 5 Hz cut off frequency, and the AP and ML components were computed [35].

For distinguishing between normal daily activities such as sitting, standing, lying, and movement, statistical properties of the amplitude of the signal are effective, but time frequency methods are more effective for distinguishing between various complex movements [2]. As one popular method, a Fast-Fourier transformation (FFT) or Short Time Fourier transform (STFT) of the whole data set can be mentioned. The advantage of this method is displaying invisible features of the data set by converting from the time domain into the frequency domain [23 , 34]. Yang et al [36] examined the most popular convertors used for image compression and audio signal separation: Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) bases. These methods used to do various datasets that were collected through real human activities and 16 types of human body movements. It was found that for ankle, knee, and thigh movements, both DWT and DCT presented similar results, which are almost linear. For the movements of elbow and wrist, the DCT provides greater performance in comparison to the DWT. For abdomen, chest, and shoulder movement, the accuracy improves linearly as in the case of leg movements (ankle, knee, and thigh) do [36].

Chapter 3: Signal Analysis

Two sections will be discussed in this chapter. In the first section, the pre-processing signal analysis such as computing the vector magnitude unit (VMU) will be presented. In the second section, three algorithms will be introduced: the adaptive Pan and Tompkins algorithm, the wavelet transform algorithm and the neural network that were used.

3.1. Preprocessing Signal Analysis

For the analysis and preparations of data based on the manufacturer's calibration specifications, these steps must be assumed: calculating the vector magnitude of the tri-axial accelerometer, filtering the noises and finally segmenting the unstable region.

3.1.1. Vector Magnitude Unit

For data analysis accelerometer outputs, each axis data set (i.e. x-axis, y-axis, and z-axis), can be measured separately. However, to compare the results of arm movements including the differences of acceleration magnitude over time, the accelerometer vector magnitude was used based on fixing the direction of the sensing unit on the human body [1, 2, 25, 35].

To best describe three-dimensional motion, spherical coordinates are usually used. The coordinate system is shown in Figure 5[2]:

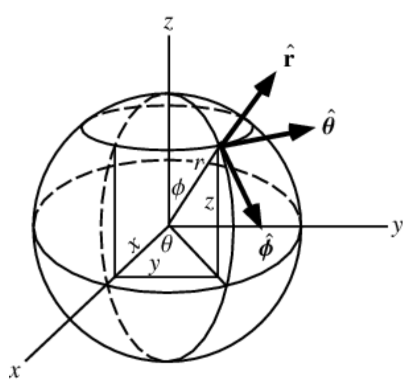


Figure 5. Relationship between Cartesian coordinates and spherical coordinates, bold arrows indicate unit vectors [2]

The three component data set is usually combined into a single value to avoid the uncertainty that results from the orientation of the sensing unit. This is indicated by equation 1 [1, 2, 13, 25, 35]:

$$r(n) = \sqrt{x(n)^2 + y(n)^2 + z(n)^2} \tag{1}$$

The angle from the z-axis to the xy plane may also be used. This angle reflects the pitch [2]:

$$\phi(n) = \tan^{-1}\left(\frac{\sqrt{x(n)^2 + y(n)^2}}{z(n)}\right) \tag{2}$$

One of the most common uses of VMU is in image processing. It does not ignore the correlation between vector components and has better results in comparison with normal methods [2].

3.1.2. Band-pass filter

Since most human movements occur in the 0.3 to 3.5 Hz range, the signals were filtered to remove unnecessary frequencies above 10Hz. For the applications where only tilt was being observed, the signal was filtered to obtain the DC values [1].

3.1.3. Moving Average Filter

When an ensemble of several realizations of an event is not available, synchronized averaging will not be possible. We are then forced to consider temporal averaging for noise removal, with the assumption that processes involved are ergodic, that is, temporal statistics may be used instead of ensemble statistics. As temporal statistics are computed using a few samples of the signal along the time axis and the temporal window of samples is moved to obtain the output at various points of time, such a filtering procedure is called a moving-window averaging filter in general; the term moving-average (MA) filter is commonly used [36].

3.1.4. Segmentation

As can be seen from previous sections, the stable (balance maintenance) regions were periods with below-average balance board activity and the unstable (balance recovery) regions were those with above-average balance board activity, where the subject is recovering from loss of balance (see Figure 6). Stable and unstable periods' segmentations differ from individual to individual and from trial to trial in amplitude, duration and shape which is the main problem of segmentation. As a result, no numerical method exists for evaluating the present state of the individual and finding a certain threshold value to find and segment the unstable periods. After segmenting the signal, other physiological data such as arm and neck movements and eyes closing or opening can be found and analyzed [1, 2].

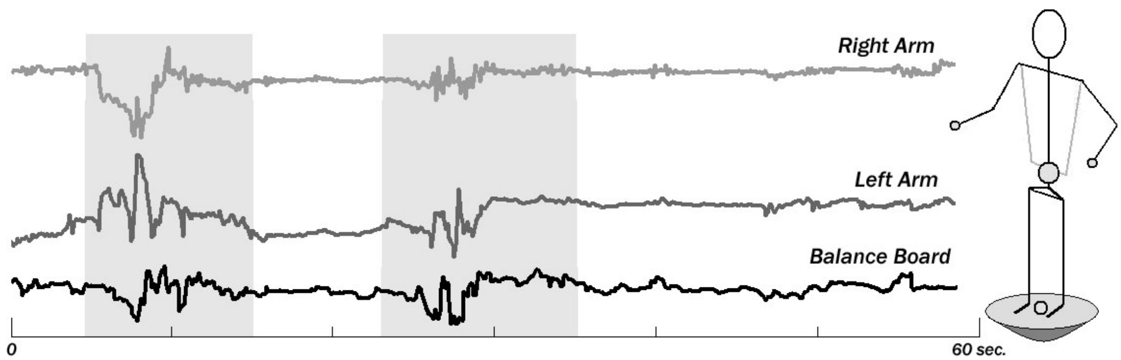


Figure 6. Segmentation of the data into Stable Regions (unshaded shaded area) and Recovery Regions (gray area) for the duration of one testing session for the balance board test [1].

The segmentation algorithm is based on finding unstable regions with a focus on high frequency and focus on balance board movement and arm movement does not finding these events without paying attention to the number and duration of their happening. Both stable and unstable regions were determined by balance board only with coordinate arm movement to balance board. Data segmentation is performed by post-hoc analysis using a custom-made Matlab program [1].

3.2. Digital Signal Analysis Algorithms

3.2.1. Balance Region Detection Algorithm

The balance region detection algorithm is based on analyzing signal slope, amplitude and width components of the balance board accelerometer signals. It is based on the adapted theory from the Pan and Tompkins algorithm for Electrocardiography (ECG) signal analysis [1, 36]. The block diagram implementation for the balance region detection algorithm is shown in Figure 7.

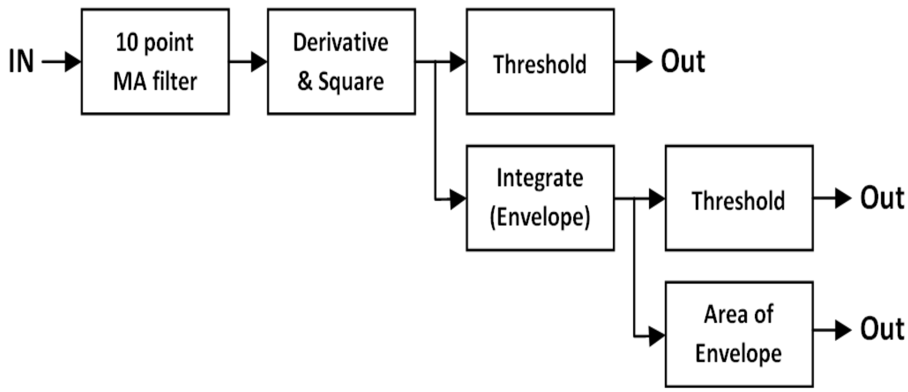


Figure 7. Block diagram implementation of the balance regions Segmentation Algorithm for detection of Stable and Recovery Regions

As mentioned in the section 3.1.2, the balance board accelerometer signal readings are pre-filtered by hardware using a low-pass filter (fc=0.16Hz) [1]. After acquisition, the algorithm is applied to segment the signal into the regions. The algorithm includes a series of filters and methods that perform moving average, derivative, squaring, integration, thresholding.

1. Noise removal: In order to reduce computational complexity and remove noise from the down-sampled signal, a 10-point moving average filter was applied to the accelerometer data, according to Equation 3 [1, 36].

$$y(n) = {}^{1}/_{10} \sum_{k=0}^{9} x(n-k) \tag{3}$$

2. Derivative & Squaring Operations: For removing the constant part of the input, which means output is equal to zero, a derivative operator can be used. Large changes in input cause the output of derivative operator to have high values. Higher frequencies receive linearly increasing gain, in other words, the derivative works as a highpass filter. Thus, the derivative operator can be used to destroy low-frequency components and improve high-frequency components [36]. Equation 4 is a good example of the derivative of the Pan and Tompkins algorithm for signals up to 30Hz [36]. The squaring operation further emphasizes the lower values (high-frequency components), which are due to the loss of balance, and takes the absolute value of the signal [1].

$$y(n) = {}^{1}/_{8}\,[2x(n) + x(n-1) - x(n-3) + 2x(n-4)] \tag{4}$$

3. Integration Operation: The output of derivative based operation will display multiple peaks within the duration of a recording. To obtain a smooth output of the preceding operation, the Pan-Tompkins algorithm uses a moving–window integration filter. The moving-window integration filter performs an enveloping operation, which helps to easily recognize the multiple regions of balance loss during the duration of recording. A window size of N=80 was found to be ideal for exactly highlighting the regions of balance loss for this type of signal independently of their frequency of occurrence, duration and magnitude. The implementation of the filter can be seen in Equation 5 [1, 36].

$$y(n) = {}^{1}/_{N}\,[x(n-(N-1)) + x(n-(N-2)) + \cdots + x(n)]] \tag{5}$$

4. Thresholding: To find instability or recovery sections, a thresholding procedure is used. Thresholding can be estimated by user experience or by defining input value. This allows the user to define the sensitivity of the selection to reflect the individual subjects' differences and their abilities to maintain balance on the balance board [1].

3.2.2. Fourier Transform

As a famous mathematical tool to transfer the time domain signal to the frequency domain to analyze and characterize signals in the frequency domain, the Fourier series and the

Fourier transform (FT) can be named [37, 38]. The Fourier series is suitable for expressing and analyzing a periodic signal by assuming an infinite series of a weighted sum of harmonically sinusoidal (orthogonal sin(kx), cos(kx)) components. The strengths of sinusoidal components and the power of the equivalent sinusoidal are represented by the weighting coefficients and magnitude squared of each weighting coefficient respectively. For a signal x(t), the FT is given by [2, 37, 38, 39 , 40]:

$$X(f) = \int_{-\infty}^{\infty} x(t)e^{-j2\Pi ft}dt \tag{6}$$

For the aperiodic signals with a finite-length sequence, which can be one period of a periodic sequence that can be named as a discrete signal, FT can be used for presenting their spectral characteristics with finite energy. FT is an extension of the Fourier series and is an example of an integral transform. Also FT can convert a discrete time signal to a continuous function. Discrete Fourier Transform (DFT) is defined as [2, 38, 40] :

$$X[k] = \frac{1}{N}\sum_{n=0}^{N-1} x(n)\ e^{-j2\Pi kn/N} \qquad k=0, 1, 2, ..., N-1 \tag{7}$$

In turn, for converting the signal from frequency to the time domain, an Inverse Discrete Fourier Transform (IDFT) can be used [2, 37, 38, 40]:

$$x(n) = \frac{1}{N}\sum_{k=0}^{N-1} X(k)e^{j2\Pi kn/N} \qquad n=0, 1, 2, ..., N-1 \tag{8}$$

Because of having few sine waves or a stationary signal in x(t), FT can find the signal’s frequency content. But, for a non-stationary signal x(t), when sudden changes occur in time, the changes spreads over the whole frequency axis in X(f). Therefore, the limitation of FT is that the signal in the time-domain is extremely restricted in time but falls over the entire frequency band and vice versa; and they cannot happen simultaneously [37, 42].

3.2.3. Short Time Fourier Transform

The Short Time Fourier Transform (STFT) was introduced to defeat the limitations of the standard FT. The advantage of STFT is that for analysis of the signal, it defines a random but fixed-length window g(t). It can do it for both stationary and non-stationary signals. In the case of a non-stationary signal, it is supposed to have an approximately stationary signal.

The STFT uses the sliding window g(t) at different times τ for decomposing the signal in a two dimensional time frequency domain S(τ,f). This can be seen in Equation 9:

$$G(f) = STFT_x(\tau, f) = \int_{-\infty}^{\infty} x(t) g^*(t,\tau) e^{-j2\Pi f t} dt \tag{9}$$

For getting windowing of the signal in STFT, filter bank analysis can be used. This modified filter bank, containing a band pass filter with central point of frequency *f* and having a window function impulse response, which is controlled by that frequency, allows the signal to pass through and be realized. The partition of frequency is identical as shown in Figure 8 [37].

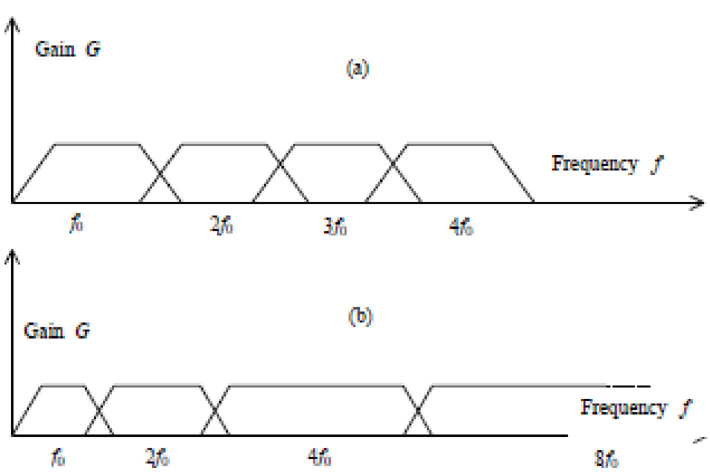


Figure 8. (a) Uniform division of frequency with constant bandwidth in STFT, (b) logarithmic division of frequency with constant-Q in WT [37]

Equations 10 and 11 can be used if both the window g(t) and its Fourier transform G(f) are centered around both the time and frequency domains. Then the ranges in time and frequency are defined in Equations 12, 13:

$$\int t\ |g(t)|^2 dt = 0 \tag{10}$$

$$\int f\ |G(f)|^2 df = 0 \tag{11}$$

$$\Delta_t^2 = \frac{\int_{-\infty}^{\infty} t^2 |g(t)|^2 dt}{\int_{-\infty}^{\infty} |g(t)|^2 dt} \tag{12}$$

$$\Delta_f^2 = \frac{\int_{-\infty}^{\infty} f^2 |G(f)|^2 df}{\int_{-\infty}^{\infty} |G(f)|^2 df} \tag{13}$$

Therefore, the time-frequency bandwidth for STFT is lower bounded by Equation 14:

$$\text{Time-Bandwidth product} = \Delta_t \Delta_f \geq \frac{1}{4\pi} \tag{14}$$

Since one particular window should be used for all frequencies, after choosing a window for STFT, the time-frequency bandwidth (resolution) will be constant over the entire time-frequency plane. In STFT there is always a balance between time and frequency resolution [37].

3.2.4. The Wavelet Transform

The Wavelet Transformation (WT) plays an important role in the study of self-similar signal systems. The wavelet transform provides the normal method, for the effect of self-similar or scale-invariant signals and as a wavelet-based representation; it is a great practical method for measuring time for the progress of frequency complex transients [2, 41]. Also, they are used to identify sharp signal movements [2]. On the other hand, as mentioned before, FT with its fast algorithms (FFT) is used for analysis and processing of many natural signals such as translation-invariant, stationary and periodic signals [39, 41].

The Fourier transform diagnoses any convolution-type operator, and this property has been an advantage of Fourier transform methods in deconvolution problems such as Equation (15) [42].

$$Y = f + Z \tag{15}$$

f shows a signal which must satisfy $f \in L^2(R^d)$ and z shows mean zero Gaussian noise.

The disadvantages of the Fourier transform are the lack of smoothness and time resolution. The FT leads an unacceptable decision based on assuming low-frequency structure as information, and high-frequency structure as a noise from f in Equation 15. As another disadvantage, FT has certain limitations to characterize many natural signals, which are non-stationary (e.g. music, speech, images). However a time varying, overlapping window-based FT namely STFT, is well known for speech processing applications; a new time-scale based WT can be named as a powerful mathematical tool for non-stationary signals which simultaneously represent both time and frequency from the popular Fourier transform [37, 39, 42, 43].

The classical wavelet theory is based on location of a square integral function. The Wavelet Transform searches the oscillatory functions (e.g. sine and cosine) to create the elements of the discrete transform. The oscillatory functions need to go to zero specifically when the original functions are different shifted and scaled tiny waves, named wavelets [37, 39, 43]. Wavelet analysis finds sharp movements and measures time of progress of frequency transients [2]. The Daubechies four-tap scaling functions (father wavelet) and the CDF wavelet function can be mentioned as two popular wavelet functions. These two functions are oscillatory and have value zero outside a finite interval [43]. The father wavelet function must be orthogonal on conversion and to other wavelets in its family [2].

The CDF wavelet function is a wavelet function created by Albert Cohen, Ingrid Daubechies, and Jean-Christophe Feauveau. The most frequent use of this function is in the JPEG2000 image compression standard [39]. Even though the mathematics of wavelets was introduced in the early twentieth century, the modern research in wavelet theory was begun in 1984 by French physicists Jean Morlet and Alexander Grossmann [43]. In 1988 and 1993 Ingrid Daubechies presented essentially wavelet functions transforms. They introduced $\Phi(t)$ as central function for satisfaction of number of properties [44, 45]. $\Phi(t)$ should be zero outside a limited interval and with its integer translates (e.x. $\Phi(t-k)$, $k = 0, \pm 1, \pm 2, \pm 3, \ldots$), should form a source for a specific space. $\Phi(t)$ can be calculated by [43, 44, 45]:

$$\int_{-\infty}^{\infty} \Phi(t)\Phi(t-k)dt = 0 \qquad k = 0, \pm 1, \pm 2, \pm 3, \ldots \tag{16}$$

Or, as a general formula at time **u** and scale **s** [2]:

$$Wf\ (u, s) = \langle f\ , \Phi_{u,s} \rangle = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} f(t) \Phi^* \left(\frac{t-u}{s} \right) dt \tag{17}$$

The main advantage of wavelet transform is smoothness characterization. It means that the membership of a function can be determined in many different function spaces by examining its wavelet coefficients. This characteristic is useful in several applications such as image processing, statistical applications, data compression and noise removal. Other advantages such as non-redundancy, fast, and simple implementation with digital filters using micro-computers have popularized the DWT in many signal processing applications since the last decade [37, 42].

Scalogram is the name given to the graph of magnitude of the WT and is important for recognizing signal characteristics at different times (u) and scales (s). For defining distribution energy, which stipulates the position of energy of the signal in time and frequency, the square of the magnitude of WT can be used [2]:

$$E\ (u, s) = |Wf\ (u, s)|^2 \tag{18}$$

.

For following the signal's frequency sequential movement, the peaks of the Wavelet Transform can be used. This can happen because of the nature of wavelet which has a fixed duration in contrast to the FT that has unlimited sinusoidal waveforms [2].

3.2.4.1. Definition of Wavelet

As mentioned before, a small wave with focused energy in time is called 'wavelet'. Because it has an oscillating wavelike specification, it is able to analyze both time and frequency simultaneously. Also, transient, non-stationary or time-varying signals can be analyzed by the wavelet [38]. In Figure 9 both wave (sinusoids) and wavelet are shown.

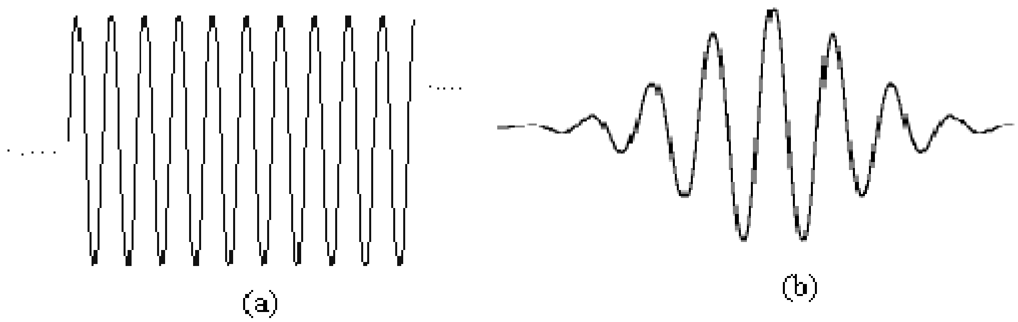


Figure 9. Representation of a wave (a), and a wavelet (b) [38]

Waves are smooth, predictable and everlasting. The primary use of waves is in the Fourier analysis as their deterministic basis functions for the development of signals or functions. On the other hand, wavelets are time-invariant or static with limited duration, uneven and may be unequal [38].

3.2.4.2. Wavelet Analysis

An 'Analysing wavelet' or 'mother wavelet' is a wavelet original function which is implemented for wavelet analysis. Time-based analysis is accomplished with a contracted, high frequency version of the original wavelet, though frequency analysis is achieved with an expanded, low frequency version of the same wavelet. The WT pair is found by mathematical formulation of signal expansion using wavelets, which is similar to the FT pair. DWT has a similar structure with DFT. Similar to FFT algorithms; it has a well-organized application through fast filterbank algorithms [37].

3.2.4.3. Structure of Wavelet Transform (WT)

There are two different kinds of WT: continuous (analog) and discrete form. Continuous wavelet transform (CWT) with both deterministic and non-deterministic bases is an effective tool for both analysis and characterization of signals and distinctiveness detection. Discrete wavelet transform or the standard DWT is discrete and fast application of CWT that has a real valued basis. DWT is a non-redundant transform and the signal has the same data size in the transform domain. To realize the standard DWT, a simple filterbank structure of recursive FIR filters can be used. The filter bank or DWT is composed of constant bandwidth (constant

Q) with constant Δ_f/f of bandpass filters. So, with changing Δ_f with frequency, time resolution Δ_t must change logarithmically to modify itself and adopt to the new condition. Multiresolution Analysis (MRA) is a very important characteristic of DWT at different resolution levels that helps DWT to view and process various signals. One of the limitations of STFT is having fixed resolution. To solve this problem MRA can be defined by assuming that resolutions Δ_t and Δ_f vary in the time-frequency plane [37].

The CWT form of WT arranges a flexible time-frequency window, which gets smaller with observing high frequency events that time resolution effects, and becomes enlarged with evaluating low frequency behavior with good effects on frequency resolution. So based on this characteristics, this kind of analysis is good for short high frequency and/or long low frequency especially in practical situations [46].

Theoretical Aspects of Wavelet Transform

From shifting and scaling of the mother wavelet $(\Phi\ (t)\ \in L2(\Re))$, many other functions can be found as:

$$\Phi_{u,s} = \frac{1}{\sqrt{a}}\ \Phi\left(\frac{t-u}{s}\right) \tag{19}$$

Where u , s $\in (\Re)$ (s>0). Parameter s is a scaling factor and u is a shifting factor.

Satisfying $\left\|\Phi_{u,s}(t)\right\| = \|\Phi(t)\|$ is one condition for normalization and as another condition for the mother wavelet, it should fulfill an admissibility condition to have bandpass behavior [37].

$$C_{\Phi} = \int_{-\infty}^{\infty} \Phi(t)dt = \boldsymbol{\varphi}(0) = 0 \tag{20}$$

Which $\varphi(w)$ is the Fourier form of $\Phi(t)$. The CWT is also defined as:

$$CoWT_f(u,s) = \int_{-\infty}^{\infty} \Phi_{(u,s)}{}^{*}(t) f(t) dt = \langle \Phi_{(u,s)}(t), f(t) \rangle \tag{21}$$

Increasing scale s means enlarging $\Phi_{(u,s)}$(t) in time to have a long term behavior of the associated signal f (t). On a large-scale, the view of the signal is global while on a small scale is visible. This means the scale shows the frequency resolution since the resolution of continuous time signals cannot be modified by themselves based on the ability of scale inverting.

CWT contains a set of wavelet coefficients (CWT_f (u,s)) which specify the similarity of the signal to some specific basis function. These help to recover f(t) from its transform by Equation (22) [37]:

$$f(t) = \frac{1}{C_\Phi} \iint_{-\infty}^{\infty} CWT_f(u,s)\Phi_{u,s}(t)\,\frac{duds}{u^2} \tag{22}$$

The disadvantage of CWT is its inability to communicate with digital computers. Hence, these parameters are measured on a discrete time-scale, which causes a discrete set of continuous basis functions based on [37]:

$$u = a_0^j \quad , \quad s = k\ a_0^j b_0 \quad \text{j, k} \in \text{Z} \tag{23}$$

a>1 means a dilated step and b≠ 0 is a translation step. The family of wavelets then becomes:

$$\Phi_{j,k}(t) = a_0^{-j/2}\Phi(a_0^{-j}t - kb_0) \tag{24}$$

and for recovering f(t):

$$f(t) = \sum_j \sum_k D_f(j,k)\Phi_{j,k}(t) \tag{25}$$

where the 2-dimensional set of coefficients D_f (j, k) is called the DWT of a given function f(t). Figure 10 shows the most famous form of discretization with a=2 and b=1 named as the standard DWT. For discretization $\Phi_{j,k}$ must be an orthonormal basis of L^2 ($\Re$) and:

$$D_f(j,k) = \int_{-\infty}^{\infty} \Phi^*{}_{j,k}(t) f(t)dt = \langle \Phi_{j,k}(t)\ f(t) \rangle \tag{26}$$

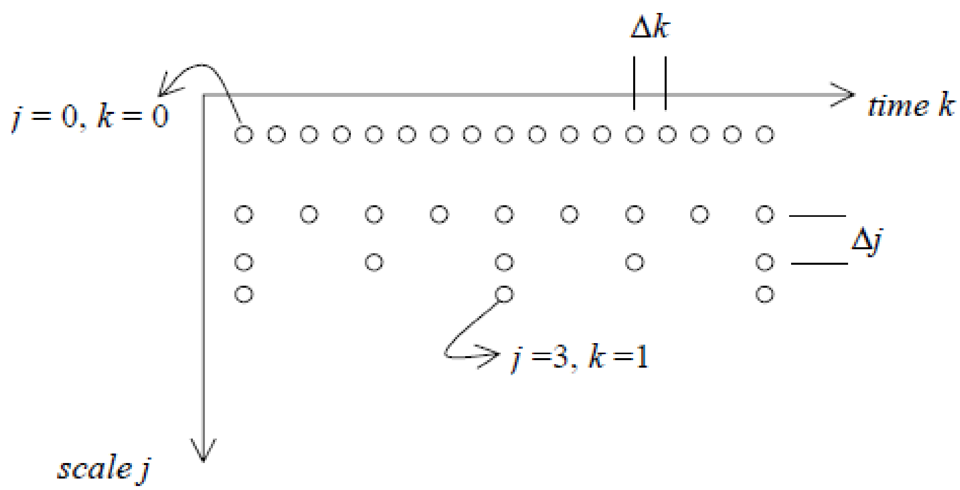


Figure 10. Standard DWT on time-scale grid [38]

3.2.4.4 Filterbank Implementation

For having the effective lower resolution coefficients, wavelet coefficients which describes details ($D_f(j,k)$) and scaling or approximations coefficients ($C_f(j,k)$) of the mapped signal *f*(*t*) onto both V_j and W_j should be resulted recursively from Equations 29 and 30 with MRA concept as [38]:

$$C_f(j+1,k) = \sum_n h_0[n-2k]C_f(j,k) \qquad (31)$$
$$D_f(j+1,k) = \sum_n h_1[n-2k]D_f(j,k)$$

Figure 11 presents a tree- structured filterbank that derived from Equation 31. As can be seen, in the standard DWT each successive decomposition level causes the size of scaling and wavelet coefficients to drop by a factor of 2. Since the wavelet characteristic is orthonormal, the lower level resolution scaling and wavelet coefficients can create the next immediate high resolution scaling coefficients as [37]:

$$C_f(j,k) = \sum_n h_0[k-2n]C_f(j+1,n) + \sum_n h_1[k-2n]D_f(j+1,n) \qquad (32)$$

The recursive synthesis similar to Equation 32 which is a reconstruction of a filterbank structure is implemented in Figure 12. It can be recreated with equal and time reversal of h_0 and h_1 filters named as $\tilde{h}_0$ and $\tilde{h}_1$. By putting zeros between each sample of $\tilde{h}_0$ and $\tilde{h}_1$, $C_f(j,k)$ can be acquired, the next scaling coefficients can be found by implication of h_0 and h_1 filters [2, 37].

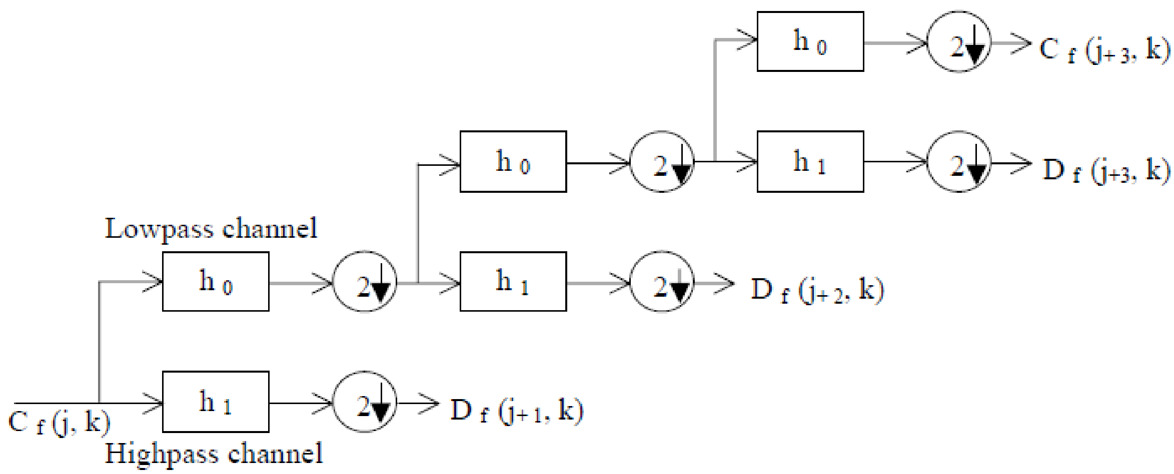


Figure 11: Two-channel, three-level analysis filterbank with 1-D DWT [37]

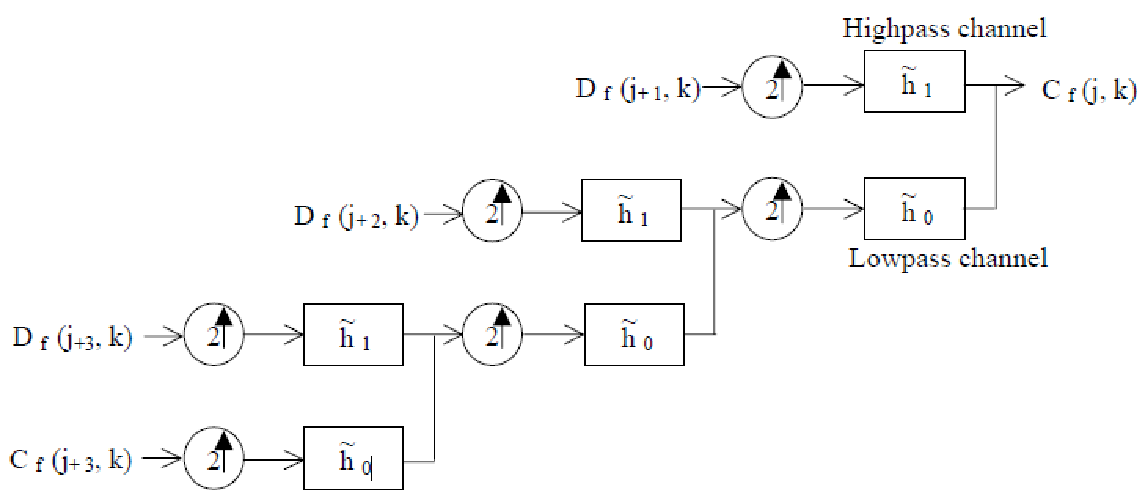


Figure 12. Two-channel, three-level synthesis filterbank with 1-D DWT [37]

The perfect reconstruction or proper recovery of signal is the most important principle of filterbank implementation of DWT. For analysis and synthesis filters the perfect reconstruction executes certain limitations which share the filters to either orthogonal wavelet bases or to the biorthogonal wavelet bases [37].

3.2.4.5 Research Algorithm

The algorithm is based on analyzing signal slope, amplitude and width components of the arms and balance board accelerometer signals. For this project Daubechies-2 (db2) wavelet with level 1 is used since it could detect sudden changes and motions in the signal and no further transform levels were executed as this would only consume processing time. In general dbn shows the Daubechies Wavelet family and n is the order. The Haar wavelet, db1, is another member of the wavelet family [47]. db2 is less computationally expensive. The Haar wavelet in some cases similar results but in some signals the results are worse than, which makes db2 to be more preferable.

The block diagram implementation for the balance regions detection algorithm is shown in Figure 13.

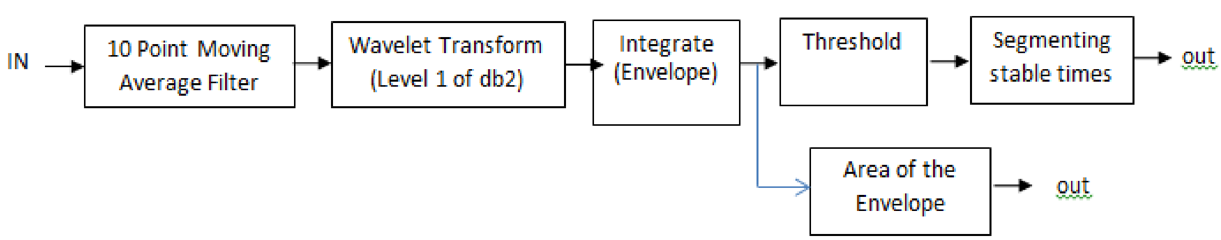


Figure 13. Block diagram implementation of the Wavelet Transform Algorithm for detection of Stable and Recovery Regions

Lowpass filter with cut off frequency of 0.16Hz was used at the beginning of the data acquisition. After that, the proposed algorithm was applied to segment the signal instability. The algorithm includes a series of filters and methods that perform a moving average, the wavelet transform db2, squaring, integration, and thresholding.

1.Noise removal: a 10-point moving average filter was used to remove noise and reduce computational complexity. This can be seen in Equation 33 [1, 36].

$$y(n) = {}^{1}/_{10} \sum_{k=0}^{9} x(n-k) \tag{33}$$

2. Wavelet Transform: The level-1 of db2 is used for removing stable part of inputs. Having large changes in input, the output has higher values. The WT destroys stable regions with low frequency and emphasizes high frequency components that show unstable parts of the signal. The squaring operation further emphasizes the high-frequency components and takes the absolute value of the signal.

3. Integration Operation: The output of the wavelet transform operation will display multiple peaks within the duration of a recording. Then the moving-window integration filter with a size of 80 is used to perform an enveloping operation to easily recognize the multiple regions of balance loss. The implementation of the filter can be seen in Equation 34 [1, 36].

$$y(n) = {}^{1}/_{N} \left[x\big(n-(N-1)\big) + x\big(n-(N-2)\big) + \cdots + x(n)\right]] \tag{34}$$

4. Threshold: For finding instability or recovery sections a threshold is used. The threshold adapts itself automatically with the signal based on the 90% value of the signal's peak. If it is greater, then it is divided by 2. The algorithm would stop when the peak becomes lower than 90% of that threshold.

5. Segmenting stable times: After a threshold is calculated, all sections with amplitudes lower than the threshold were considered stable and set to zero. Non-zero amplitudes now represent movement or unstable sections of the signal. To detect the starting and finishing time of the instability areas where major movement occurs, a count of the number of zeros in the high pass signal is used. In this case 27 zeros are used to segment the signal; counting starts from the last peak until 27 zeros are reached, then the last pick is assumed to be end of the movement.

3.2.5. The Neural Network Classification

Using an artificial neural network is one of the biggest interests in recent years for implementing complex functions in different fields of domains such as estimation, identification, prediction or optimization, control and signal classifications [48, 49]. Also, they can be seen in normal life equipments such as cell phones, and TV sets [50].

A neural network (NN) as a parallel-distributed processor has a natural tendency to store practical information and to use it in essential times. It has two similar characteristics with the brain [49]:

- Information can be developed by the network based on a learning procedure.
- For storing information, some inter-neurons powers called synaptic weights are used.

In theory, the NN has the same ability as a normal digital computer [49]. Learning based on examples or supervised learning is a great advantage of the artificial neural networks [51]. In traditional solving algorithms, at first a model must be created and developed and then a series of operations of the problem solving algorithm has to be indicated. These algorithms have a problem in facing practical problems with a high level of complexity since sometimes it is difficult or even impossible to create a powerful algorithm for them.

On the other hand, in the models such as NN, they do not use a solving algorithm devoted to a problem; they just use and train a set of reliable examples to learn and generalize them to get to the particular target output by extracting the information from them [49, 51]. One NN adjust system is shown in Figure 14. In this way, the NN creates an algorithm to solve a problem by itself which is indirectly a certain model of a problem [51]. Then, the output and target are evaluated and the network tunes till they equal each other. In this method, there are many input/target pairs to train a network. With enough training examples and enough computing resources, the NN can be trained perfectly to implement almost any mapping to a random level of accuracy [49].

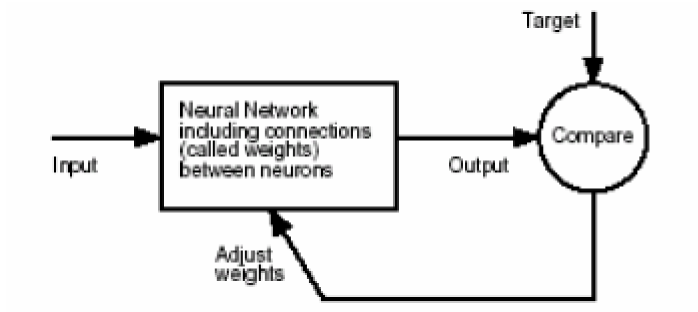


Figure 14. Neural Network adjust system [49, 52]

3.2.5.1 The Neuron Model and Architectures

<u>The neuron</u>

The single layer perceptron is the simplest NN since it has just two possible classes for an input. A schematic diagram of a perceptron is shown in Figure 15. $F(u_j)$ is called the transfer function (TF) any network output is moved through it and is nonlinear. There are different types of TF such as sigmoidal logistic function, linear function, and …[49].

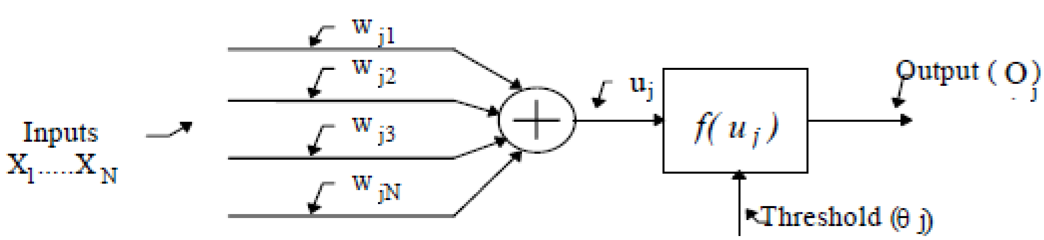


Figure 15. Neural Model [49]

The classical biological neuron's process is that a total of the incoming signals are maintained in the cell's dendrites. When a new pulse is distributed by the neuron, it means the total number of the incoming signals goes above a certain threshold. Then, this new pulse is spread along its axon. In another case, the neuron remains inactive.

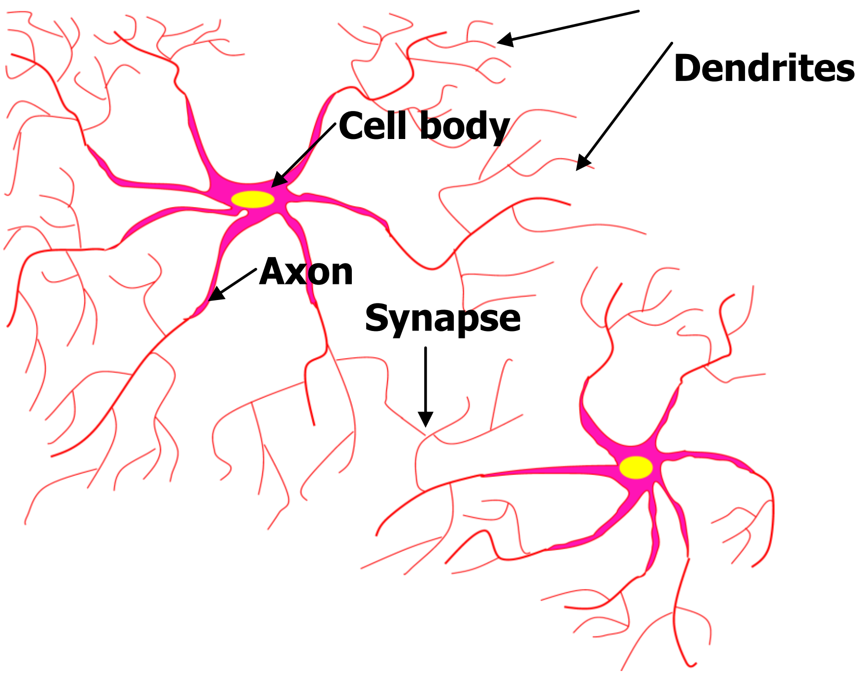


Figure 16. Biological neuron [53]

$$u_j = \sum_{i=1}^{N} w_{ji} x_i \tag{35}$$

$$O_j = f(u_j - \theta_j) \tag{36}$$

In Equations 35 and 36, for categorizing each set of synapses, a weight or strength of each synapses is used. For a signal X, the input of synapse i connected to neuron j is multiplied by the synaptic weight w_{ji}. The sequence of the subscripts' w_{ji} is important. The first subscript identifies the neuron and the second subscript refers to the input at the end of the synapse which the weight refers to. Transfer function stimulates the associated synapse, caused the weight w_{ji} to become positive. When the associated synapse is restricted, the weight w_{ji} becomes negative. A transfer function is restricted by the amplitude of the output of a neuron. The transfer function is a pressing function that keeps the acceptable amplitude range of the output signal in some finite value [49].

Transfer Function

The transfer function is the function $F(u_j)$ which is based on the net input and bias, and defines the output of the neuron. There are many different types of transfer functions such as linear, step, and ramp function as can be seen in Figure 17. In general, mappings are monotonically increased by transfer functions except the linear function, where [49, 53]:

$$f_u(-\infty) = 0 \qquad or \qquad f_u(-\infty) = -1 \tag{37}$$

$$f_u(\infty) = 1 \tag{38}$$

The most commonly used functions are log-sigmoid, tan-sigmoid and linear transfer functions. Multi-layer networks often use the log-sigmoid transfer function as shown in Figure 18 by:

$$f_u = \frac{1}{1+e^{-\lambda(net-\theta)}} \tag{39}$$

The tan-sigmoid transfer function is described as:

$$f_u = \frac{1-e^{-\lambda(net-\theta)}}{1+e^{-\lambda(net-\theta)}} \tag{40}$$

And the linear transfer function is used as shown in Figure 19:

$$f_u = f(s) = s \tag{41}$$

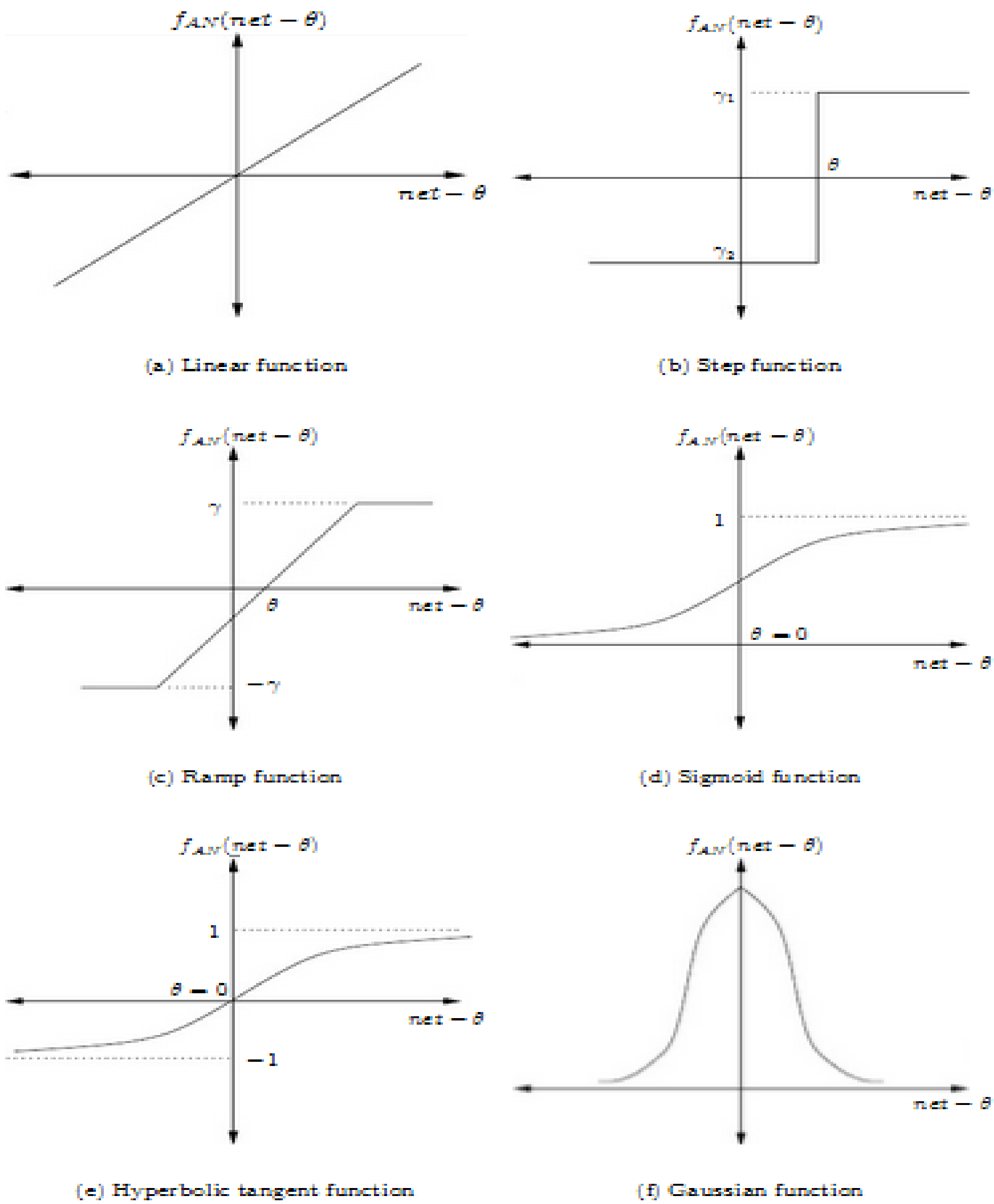


Figure 17. Transfer Functions [53]

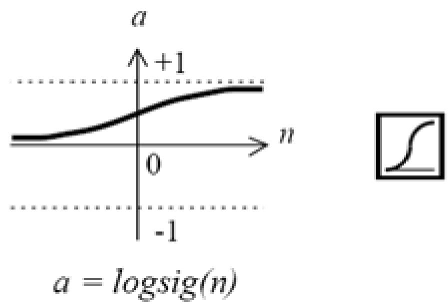


Figure 18. Log-Sigmoid Transfer Functions [49]

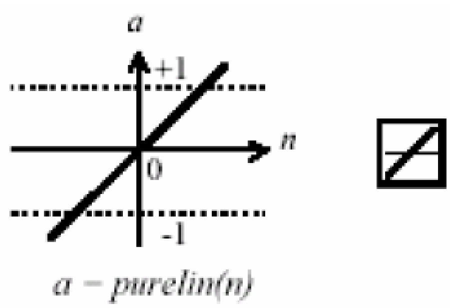


Figure 19. Linear Transfer Functions [49]

For any input with any value between plus and minus infinity, the sigmoid transfer function mauls it into the range of 0 to 1.Since this transfer function is differentiable , the more common use is in back-propagation networks [49].

Single-layer feed forward network

A network of neurons which is organized in the form of layers is called a layered neural network. The simplest form of a layered network is a feed forward type of the network with source nodes in an input layer that connecting to an output layer of neurons but not vice versa. It is shown in Figure 20 with R input elements and S neurons. The network called 'single-layer' because of the output layer of working out nodes, not the source nodes since no computation is completed there [49].

The single-layer network weight matrix, $\mathbf{W_p}$, helps each neuron input to connect to each element of the input vector **p**. The scalar output n(i) is formed by summation of weighted inputs and bios of the ith neuron. An S-element of vector **n** from the net input vectors is formed by convolving different n(i). Finally, a column vector **a** is formed by the neuron layer outputs as shown at the bottom of the Figure 20. It is very common that the number of inputs in a layer is different from the number of neurons in that layer [49, 53, 54, 55].

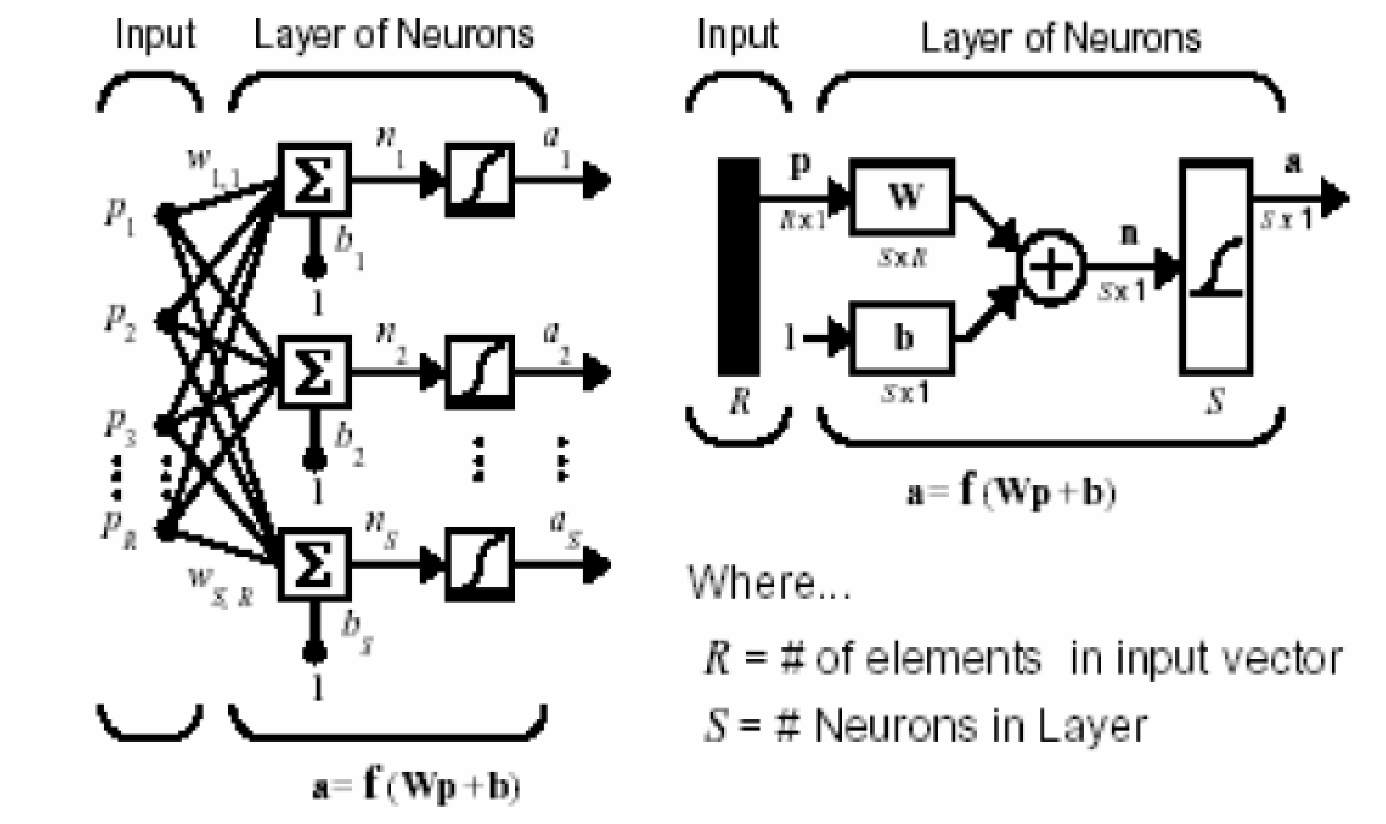


Figure 20. Single-layer feed-forward network [53, 54, 55]

Matrix- vector input

Figure 21 shows a neuron with a single R-element input vector, p_1,p_2,…,p_R. As can be seen, each element of the inputs are multiplied by weights $w_{1,1}$, $w_{1,2}$, $w_{1,3}$,…, $w_{1,R}$, resulting in the source of the summing junction. The sum is W_p ,which is found by the dot product of the single row of matrix **W** and the vector **p**. To form the net input n, the neuron's bias, b, is added to the weighted inputs. This sum, n, is the independent variable of the transfer function f.

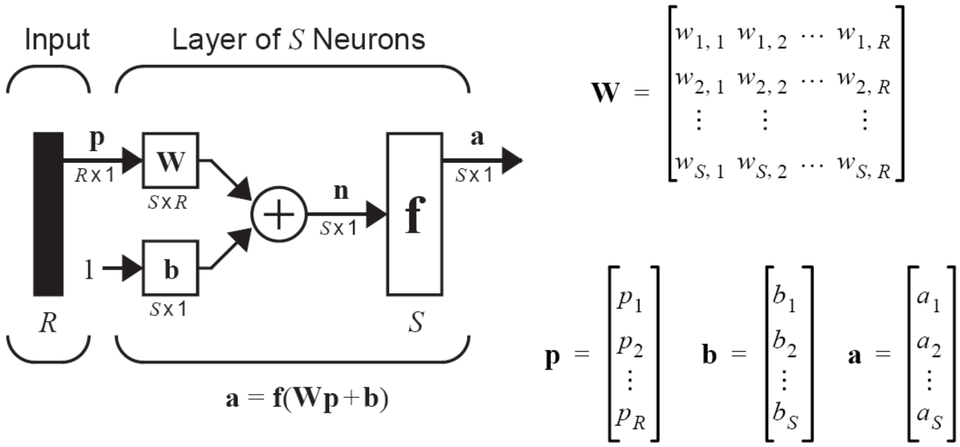


Figure 21. A neuron with a single R-element input vector. R is the number of elements in the input, S is the number of neurons [53, 54, 55]

$$n = w_{1,1}p_1 + w_{1,2}p_2 + \ldots + w_{1,R}p_R + b \tag{42}$$

The combination of the weights; the vector product W_p ,which is the result of multiplication and summing operations; the bias *b*, and the transfer function *f* are defined as a "layer" of a network. But the layer does not include the array of input, vector **p**. It can be seen in Figure 21.

The weight matrix **W** helps the input vector elements to enter the network.

$$W = \begin{bmatrix} w_{1,1} & \cdots & w_{1,R} \\ \vdots & \ddots & \vdots \\ w_{s,1} & \cdots & w_{s,R} \end{bmatrix} \tag{43}$$

On the elements of matrix **W**, the destination neuron of the weight is shown by rows and to find out the input source of that weight, the column is noted. For example, the indices in W_{16} indicate a power of the sixth source to the first (and only) neuron in W_{16} [49].

Multi-layer feed-forward network

As a second class of feed forward neural networks, the multi-layer can be mentioned as can be seen in Figure 22. The difference between the multi-layer and the single-layer is the existence of one or more hidden layers with hidden neurons or hidden units that calculate the nodes. These nodes interfere between the external input and the network output. Each hidden neuron is connected to a local set of direct source code and reacts to local variants of them. Also, the neurons in the output layer are linked to a local set of hidden neurons. The advantage of these hidden layers is to allow the solution of higher-order statistics and the large size of the input layer. The layers of a multi-layer network perform various roles. An *output* layer is a layer that creates the network output. All other layers are called *hidden layers.*

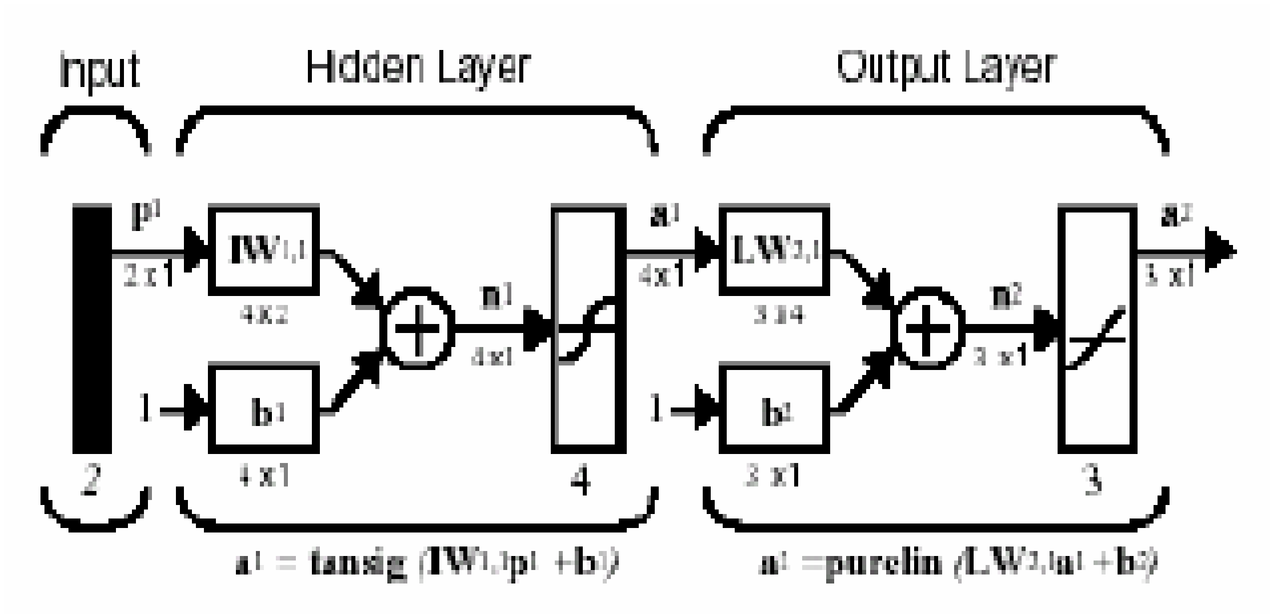


Figure 22. Multi-layer feed-forward network [52, 54]. First layer has 2 inputs and tansig function as transfer function, and output layer has 4 inputs and linear function as transfer function. The size of matrixes is written at the bottom of each matrix which is 4 for hidden layer and 3 for output layer.

A network can have several layers with a weight matrix **W**, a bias vector **b**, and an output vector **a**. To differ between layers' variables such as outputs, and weight matrices the number of the layer as an in dice is used for each of these variables. For example, the network shown above has *R1* inputs, an *s1* neurons in the first layer, an *s2* neurons in the second layer. A constant input 1 is provided for the biases of each neuron.

In each middle layer, the outputs become the inputs to the following layer. For example, layer 2 can be considered and analyzed as a one-layer network after recognizing all the vectors and matrices of layer 2 such as an *a1* inputs, an *S2* neurons, an *S1xS2* weight matrix *W2* and the output as *a2* [49, 54, 55].

Multiple layer networks are powerful. For example, a two-layer network with sigmoid and linear transfer functions for the first and second layers respectively is used widely in a back propagation neural network, with a finite number of discontinuities, can be trained to estimate any function well [49].

Nodes, inputs and layers required

The problem nature determines the number of nodes to form a decision region of the given problem; the number must be large enough but not be so large that it causes the essential weights from available data to not calculate. In perceptron networks, like feed-forward networks, three layers are enough since they can create complex decision regions.

In the second layer, when decision regions are incoherent and a curved area cannot form them, the number of nodes must be more than one. The number of its nodes in the worst case should be equal to the number of input distributions' disconnected regions. In the first layer the number of nodes must be sufficient to provide three or more edges for each curved area generated by every second-layer node. Normally, the number of nodes in the second layer must be three times more than the first layer [49].

Training Algorithms

1. Back-propagation

Back-propagation (BP) is a gradient decent algorithm that is produced by applying the Widrow-Hoff learning rule, also known as the delta or least mean squared (LMS) rule, to multiple-layer networks and the nonlinear differentiable transfer function. For training a network both input vectors and the corresponding output vectors are involved. The training procedure is done when it estimates a function, companion input vectors with specific output vectors, or classify input vectors. The other standard optimisation methods such as conjugate gradient and newton methods are basic algorithms [49, 52, 55].

As can be seen in Figure 22, a feed-forward network with hidden layers usually is called the BP neural network. The used TF for these nodes is the sigmoid function and the output from each node is given by [52]:

$$\sigma_i^k = F(a_i^k) \tag{44}$$

The total input to node i is given by a_i and is:

$$\sigma_i^k = \sum_{j=1}^{n} w_{ij} a_j^k + \theta_i \tag{44}$$

The order of the weight index is important. For example, the weight of the connection from node j to node i can be written as w_{ij} . After that for network training, the error of the perceptron network between the target and the output must be minimized by modifying the weights. This can be achieved by:

$$\Delta_k W_{ij} = -\propto \frac{\partial E^k}{\partial W_{ij}} \tag{45}$$

where the mean square error for the k[th] pattern is shown by E^k. The method that the back-propagation uses is based on calculating the error for a hidden node i from the errors of the nodes connected to it. In summary, the change in the hidden node i's weight, W_{ij}, can be changed as given by [52]:

$$\begin{aligned} \Delta_k W_{ij} &= \propto \delta_i^k \sigma_j^k \\ &= \propto (\acute{F}(a_i^k) \textstyle\sum_{n=1}^{\acute{N}_{p+1}} \delta_n^k w_{ni}) \sigma_j^k \\ &= \propto (\sigma_i^k (1-\sigma_i^k) \textstyle\sum_{n=1}^{\acute{N}_{p+1}} \delta_n^k w_{ni}) \sigma_j^k \end{aligned} \tag{46}$$

The changes in the weights of the network explain the delta rule for defining weight changes between layers especially between output layer and the hidden layer. Since through the network the errors are provided for backward or back propagated, this network is called BP.

The most useful feature of a BP network is simplification. Because of the network's training method which requires target and data prior, a set of input patterns can be structured into groups and provided for the network. Then, the patterns in each group will be "observed" and the network will be trained to recognize the characteristics of that specific group. Based on these characteristics the trained network will know how to accurately group data and ignore the irrelevant data [38, 52].

2. <u>Conjugate Gradient Algorithm</u>

The basic BP algorithm modifies the weights for the gradient's negative values of the gradient way. The resulting of the gradient descent, the performance function, is decreasing most rapidly. But, it does not mean it creates the fastest convergence. To cover this problem, the conjugate gradient algorithms which are implemented along conjugate directions are used. In most of the conjugate gradient algorithms, for each iteration along the conjugate gradient direction the step size is tuned to minimize the performance function along that line [54]. There are varieties of step size search functions such as the Fletcher-Reeves Update [49]. On the first iteration all of the conjugate gradient algorithms begin to search in the steepest descent direction (negative of the gradient):

$$P_0 = -g_0 \tag{47}$$

The next step, with the name of a line search, is to decide the optimal distance to shift the current search direction:

$$X_{k+1} = X_k + \propto_k P_k \tag{48}$$

then the next search direction is set to join the previous search direction by uniting the new steepest descent direction with the previous search direction.

$$P_k = -g_k + \beta_k P_{k-1} \tag{49}$$

The difference between altered versions of the conjugate gradient is how to find the way that the constant $\beta_k$is calculated. For example for the Fletcher-Reeves update the procedure is:

$$\beta_k = \frac{g_k^T g_k}{g_{k-1}^T g_{k-1}} \tag{50}$$

This is based on the ratio of the norm squared of the current gradient to the norm squared of the previous gradient. The advantage of the conjugate gradient algorithms is that they provide a little more storage for data than the simpler algorithms even if the result will be different from one problem to another. This makes them a good choice for networks with a large number of weights [49].

3.2.5.2 Research Algorithm

The method of computerized classification of human balance involve four major steps:

1) Pre-processing,
2) Stability detection,
3) Feature detection
4) Signal classification.

They are illustrated in Figure 23.

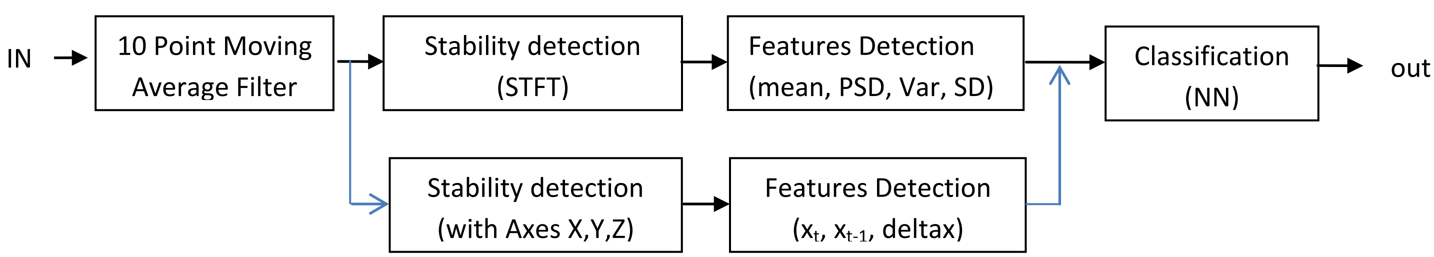


Figure 23. Block diagram implementation of the pattern recognition for classification of Stable and Recovery Regions

The first step is to measure the signal, which has both stable and unstable regions. The second step is to find the stable or unstable regions based on the frequency and time components of signal. The next step is to find features that maximize the classification performance of the following step. Because of the unknown communication of different sets of features, it is impossible to predict the optimum features for a chosen classification technique. An artificial neural network was used in this project to do the classification which was possible since plenty of data were available.

Signal Pre-processing

The data were recorded using three 3-axial accelerometers with a ±2.0g force range with a sampling frequency of 100 Hz for arms and the balance board. The noise cancellation method was a 10-point moving average filter.

Stability Detection

Two different methods were used in this report for balance detection. The first method used a short time Fourier Transform of the vector magnitude unit of the signal, and the second one used the X,Y,Z axes separately as well as the derivative of those axes.

1) **STFT:** In this method the filtered signal was used to get a VMU of the signal. Then it was divided into equal segments to have a window for better understanding of signal attributes in the frequency and time domain. The size of each window was 100 and the rectangular window was used.

2) **X, Y, Z axes:** In the second method after using a moving average filter, the individual axis in the time domain was used. The amplitude at time t and at $t+\Delta t$, and Δt were considered. The purpose of it, is to explore what change the system will face during a period of time.

Feature Extraction

After pre-processing, the second stage towards classification is to extract features from the signals. The features, which represent the classification information contained in the signals, are used as inputs to the classifiers used in the classification stage.

The goal of the feature extraction stage is to find the smallest set of features that enables acceptable classification rates to be achieved. In general, the developer cannot estimate the performance of a set of features without training and testing the classification system.

Based on previous section, there are two different kinds of features: the features can be extracted from the power spectral density (PSD), mean, variance, standard deviation and relative amplitude for each person's left arm, right arm and balance board with movement and without movement. And in the second method, each finding signal in the previous section for all patients was used as features by way of **[x;x+Δx;** Δx**; y; y+Δy; Δy; z; z+ Δz; Δz]**.

Neural Network classification

In this project, the supervised neural network was used as a method for classification. The NN that was used here is the single layer perceptron. It is a simple net that can decide whether an input belongs to one of two possible classes, stable or unstable. The back-propagation training algorithm was used in this experiment as a training function to train feed-forward neural networks to solve human balance classification. The back-propagation training algorithm is a gradient algorithm designed to minimize the mean square error between the actual output to a multi-layer feed-forward perceptron and the desired output. For network learning gradient descent a learning function with bias adjustment was used. Learning occurs according to the defined gradient, and learning rate. The weight change matrix dW, for the given neurons was calculated from the neurons' input p, error E, the weight (or bias) W, learning rate Lr:

$$dW = dW_p + Lr * gW \tag{51}$$

where, dW_p is the previous weight change matrix. It is stored and read from the learning state matrix Lr. gW is the gradient matrix with respect to performance.

The output of matrix is passed through the Log-sigmoid transfer function. The number of neurons in hidden layer is 10 for both methods. The desired output for each class is defined as the target vector. It is a set of Boolean value vectors of [1 0]. One refers to the unstable part and zero to the stable region. Choosing this target is based on using it for different subjects and data bases. The testing data, which are refer to the arms without movements, were randomly selected to evaluate the performance of the algorithms after all details of the algorithms and parameters had been finalized. Weighted input signals apply to the first layer, named input layer. The layer has biases. The last layer is the network output. The network performance is measured according to the Mean Squared Error (MSE) performance function. To compare the performance of different networks, the same conditions were kept in initializing the networks. The same training parameters and learning function were also adopted during the training process. Delta assumed to be 1, Minimum Gradient was limited to 0.00001, Maximum Epoch was 1000, and the goal was 0.005. The training set is free arm movement signals and the test signal is limited arm movement.

Chapter 4: Results

This chapter compares the results that were achieved on the balance tests with limited arms and with free arms to determine the role of arm movements and the dominant arm during maintenance of dynamic balance. As mentioned in Chapter 2, all three accelerometers were sampled at 100 Hz and Matlab software was used for developing and testing algorithms. Four subjects took part in the study.

4.1 Balance Region Detection Algorithm

Figure 24 shows the output of the balance region detection algorithm with the balance board, the unstable areas and the segmented areas for one person out of the four persons. There are some spikes in the stable areas which were caused by knee and hip muscles because of sudden movement for correcting postural balance. Perfect algorithm must have few or none of spikes.

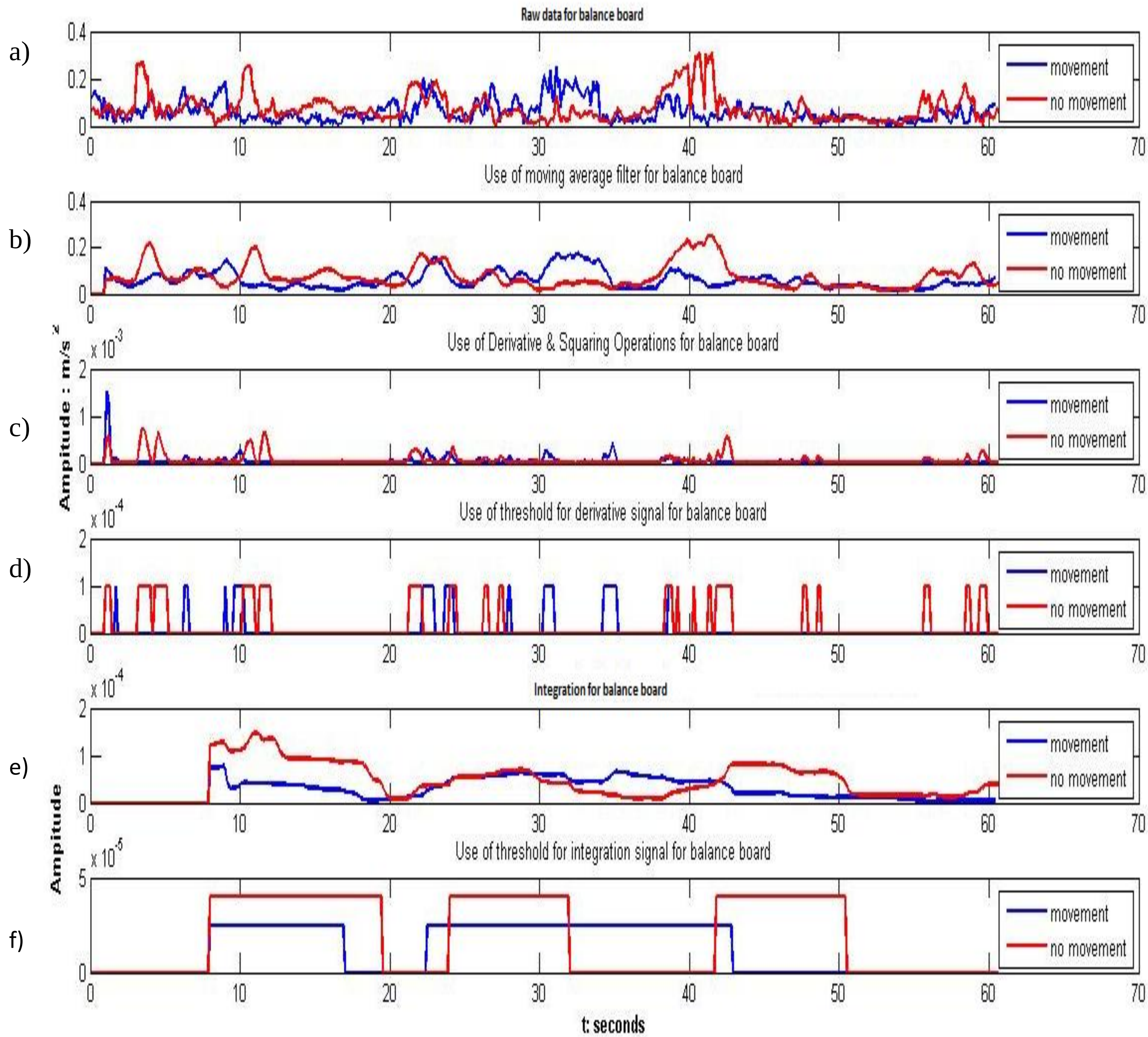


Figure 24. Balance board data from Subject 1. A) Raw Data for balance board. B) Filtering with moving average filter for removing noise and unnecessary peaks. C) Derivative and squaring of output of moving average filter to determine the regions and finding the instability. D) Using threshold to recognize the time and place of instability. E) Integration to define envelope to emphasize on unbalance regions. F) Using threshold for calculating area and duration of instability. Blue is free arm movement and Red is limited arm movement.

In Figure 24c it can be seen that with using arms a lot less instability and loss of balance occurred. Also, from Figure 24d (after derivative threshold) the place and time of improving loss of balance when arms are used to help maintain balance can be found. As is shown in Figures 24e and 24f (integral and integral threshold), when the subject did not use his arms, his balance loss was more frequent, and lasted longer.

Statistical analysis such as mean and variance of the magnitude of accelerations for arm movements during balancing tasks for the balance detection algorithm is shown in Table 1. These values are based on the entire results from the integral threshold and the combination of four participants.

Table 1. Balance Board Descriptive Statistics for all subjects

Statistic (m)	Limited Arm Movements (m)			Free Arm Movements (m)		
	Right Arm	Left Arm	Balance Board	Right Arm	Left Arm	Balance Board
Mean	0.00009	0.00007	0.00022	0.00008	0.00007	0.00023
Median	0.00016	0.00013	0.00012	0.00015	0.00013	0.00013
Variance	0.00001	0.0000051	0.00000	0.00001	0.0000053	0.00000001
Std. Deviation	0.00570	0.00457	0.00015	0.00560	0.00444	0.00016
Minimum	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Maximum	0.42310	0.33920	0.00060	0.43630	0.34830	0.00058
Area	**0.0053**	**0.0044**	**1.2973**	**0.0057**	**0.0045**	**0.0162**

The results in Table 1 suggest that the area under the integrated section is a key parameter in the balance detection algorithm which for each person discussed in Table 2.

Table 2 Calculated results of area under the integral threshold for Balance Board

Area	Limited Arm Movements			Free Arm Movements		
	Right Arm	Left Arm	Balance Board	Right Arm	Left Arm	Balance Board
Subject 1	0.0013	0.0012	0.2175	0.0014	0.0013	0.0017
Subject 2	0.0014	0.0012	0.3483	0.0014	0.00079	0.0025
Subject 3	0.0014	0.0011	0.2394	0.0015	0.0010	0.0065
Subject 4	0.0012	0.00089	0.4921	0.0014	0.0013	0.0055

As can be seen in Table 2, with the limited use of arms, Subject 4 has the greatest difference between dominant and non-dominant arm movements, as well as a low amount of arm movements. And, Subject 1 has the least difference between dominant and non-dominant arm movements, which means he used both arms equally. In contrast, in free arm movements, Subject 2 has the greatest difference between dominant and non-dominant arm movements and both Subject 1 and Subject 3 have the least difference between dominant and non-dominant arm movements.

Figures 25 and 26 illustrate the effect of arm movements and compare them with the balance board movements. Analysis of the results of arm movements from both Table 1 and

Figure 25 shows that the dominant arm has a greater area and effect than the non-dominant arm during both limited and free arm movements, which means maintenance and recovery of postural balance improved with free arm movements using arms during the loss of balance. From both Table 3 and Figure 26 it appears that when arms are used in controlling the balance, the duration and amount of loss of balance significantly less, which means the arms were used more actively.

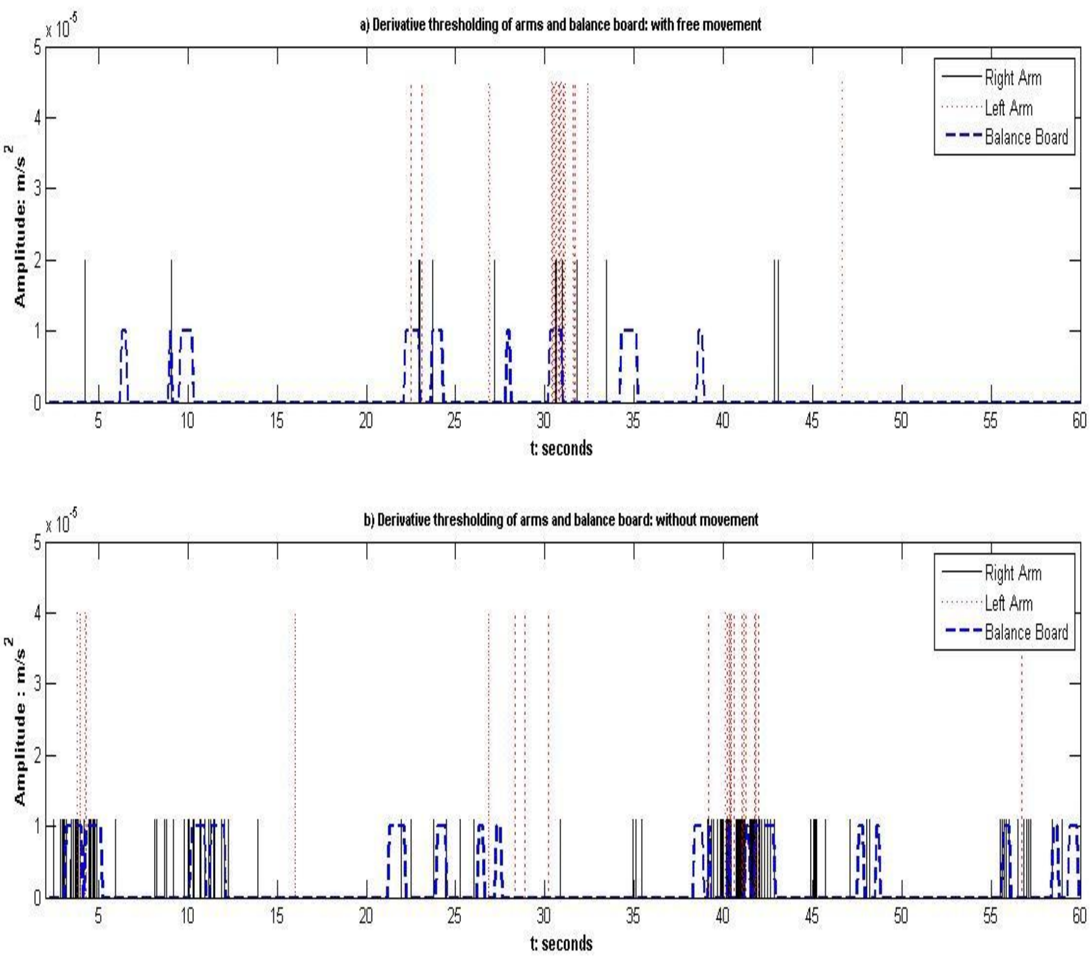


Figure 25. a) Derivative thresholding of arms and balance board with arm movement and b) Derivative thresholding of arms and balance board without movement from Subject 1

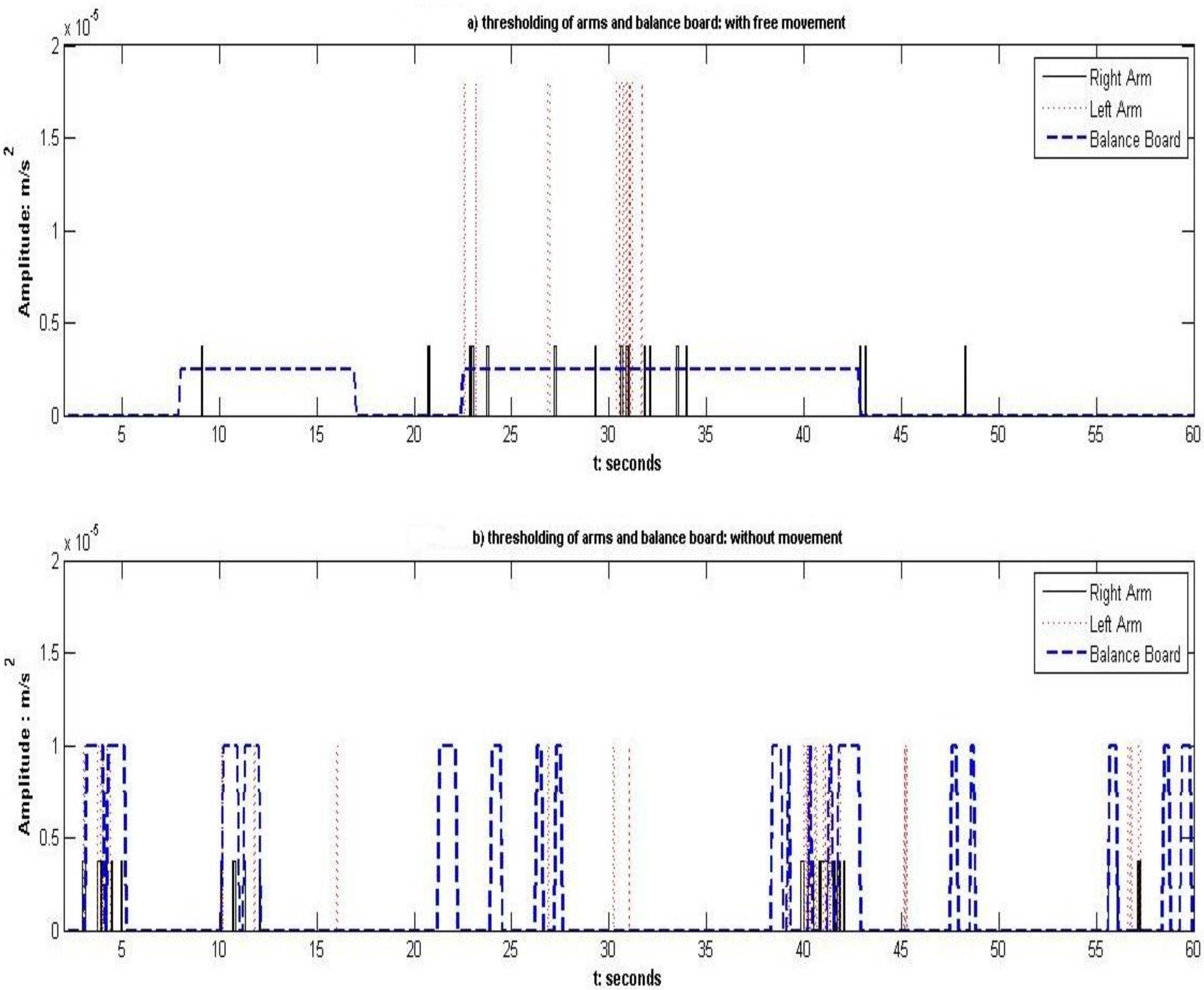


Figure 26. a) Integral threshold of arms and balance board with free arm movement and b) Integral threshold of arms and balance board without arm movements from Subject 1

In total, from Table 1 it appears that for all four of the subjects when the subjects did not use their arms, their balance loss 66.3% more often than they used their arms. The ratio between the areas of instability when arms were used versus when the arms were limited to no movement is about 98.5% and for dominant versus non-dominant arms, about 27% which means 27% more use of dominant arm. Therefore these results provide further prove of the importance of arm movement in loss of balance as well as the greater use of the dominant arm in this process. The above results were calculated based on the ratio of summation of area under the derivative thresholding and envelope thresholding for both limited arm movements and free arm movements for all subjects.

4.2 The Wavelet Transform Algorithm

Figure 27 shows the output of the wavelet transform algorithm for the balance board in the unstable regions and the segmented areas for one person. Figure 28 illustrates the effect of arm movements and compares them with the balance board movements. The high frequency wavelet component for the balance board illustrates areas of instability, as demonstrated in Figure 27c. By using zero counting that was demonstrated in Section 3-2-2 as seen in Figure 27f, instability starting and ending time is about 8 seconds and 28 seconds respectively, which is half the value of the original signal, 16 and 50 seconds respectively that shows the very similar result with integration part .

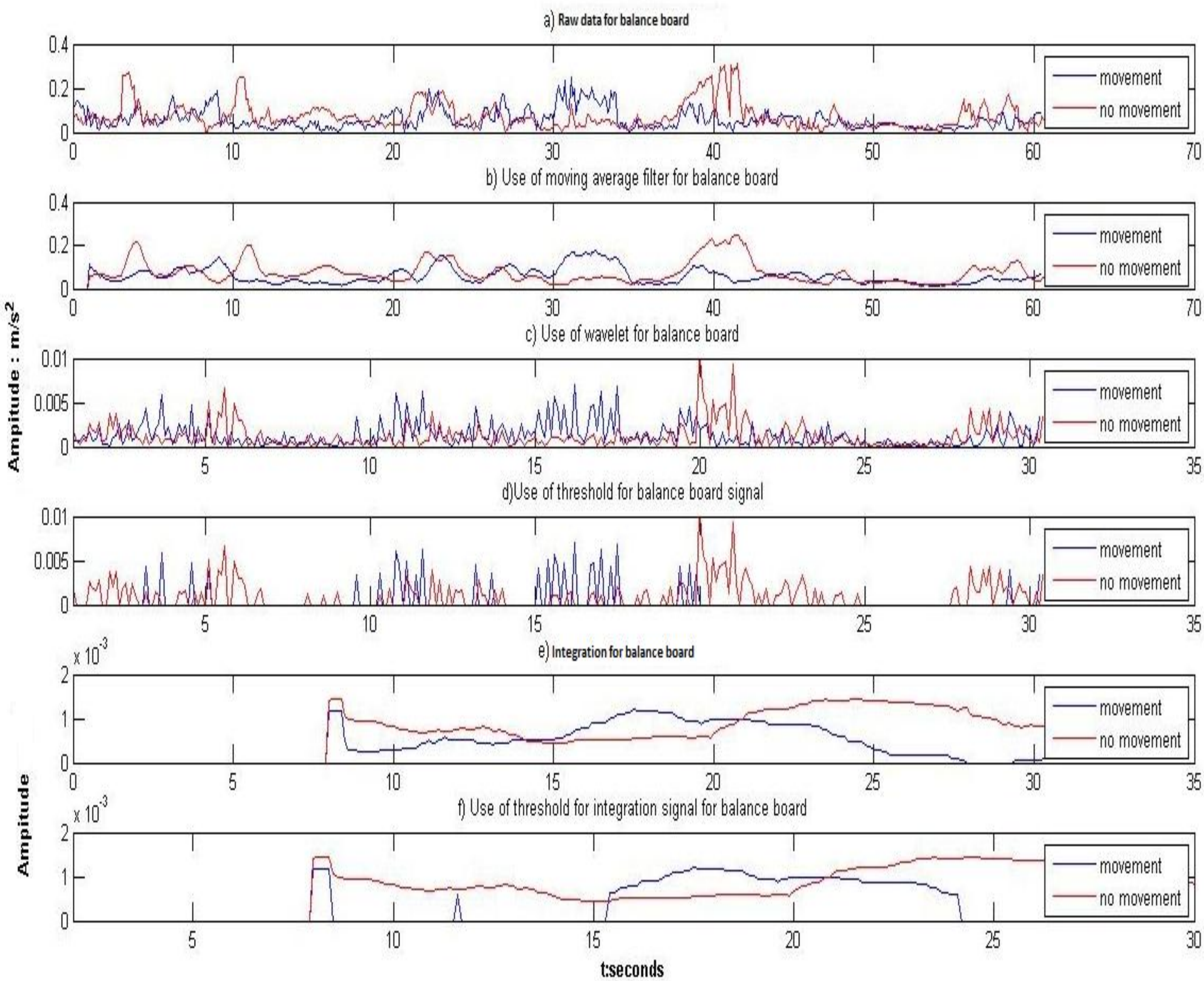


Figure 27. Balance board data from Subject 1.. A) Raw Data for balance board. B) Filtering with moving average filter for removing noise and unnecessary peaks. C) using Wavelet Transform of output of moving average filter to determine the regions and finding the instability. D) Using threshold to recognize the time and place of instability. E) Integration to define envelope to emphasize on unbalance regions. F) Using threshold for calculating area and duration of instability. Blue is free arm movement and Red is limited arm movement.

In Figure 27c it can be seen that when arms were used a lot less instability and loss of balance occurred. Also, from Figure 27d (after wavelet threshold) the place and time of improving loss of balance occur when arms are used to help maintain balance. As it is shown in figure 27e and 27f (integral and integral threshold), when the subject did not use his arms, his balance loss was more frequent, and longer.

Statistical analysis such as mean and variance of the magnitude of accelerations for arm movements during balancing tasks based on the wavelet transform is shown in Table 3. These values are based on the entire results from the integral threshold and the combination of four participants.

Table 3. Balance Board Descriptive Statistics for All Subjects

Statistic (m)	Limited Arm Movements (m)			Free Arm Movements (m)		
	Right Arm	**Left Arm**	**Balance Board**	**Right Arm**	**Left Arm**	**Balance Board**
Mean	0.00057138	0.00283305	0.01817726	0.00109462	0.00125985	0.01151534
Median	0.00074259	0.00109200	0.00940926	0.00172457	0.00078312	0.00695122
Variance	0.00000143	0.00000086	0.00003987	0.00000570	0.00000059	0.00002474
Std. Deviation	0.00190007	0.00182568	0.01119015	0.00390237	0.00145732	0.00880187
Minimum	0.00000000	0.00000000	0.00000000	0.00000000	0.00000000	0.00000000
Maximum	0.04301505	0.04250000	0.03260000	0.05630000	0.04144925	0.02940000
Area	**0.0380**	**0.0142**	**0.5544**	**0.0561**	**0.0308**	**0.411**

The results in Table 3 suggest that the area under the integrated section is a key parameter in the wavelet transform which is discussed for each person in Table 4.

Table 4. Calculated results of area under the integral threshold for Balance Board

Area	Limited Arm Movements			Free Arm Movements		
	Right Arm	**Left Arm**	**Balance Board**	**Right Arm**	**Left Arm**	**Balance Board**
Subject 1	0.0032	0.0028	0.0205	0.0039	0.003	0.0126
Subject 2	0.0049	0.0012	0.2104	0.0217	0.0109	0.1438
Subject 3	0.0101	0.0084	0.172	0.0061	0.0015	0.094
Subject 4	0.0198	0.0018	0.1515	0.0244	0.0154	0.1606

As can be seen in Table 4, during the limited use of arms Subject 4 had the greatest difference between dominant and non-dominant arm movements, as well as the greatest amount of arm movements. And, Subject 1 had the least difference between dominant and non-dominant arm movements which means he used both arms equally, as well as the lowest amount of balance board movements. In contrast, in free arm movements, Subject 2 had the greatest difference between dominant and non-dominant arm movements and Subject 1 had the least difference between dominant and non-dominant arm movements.

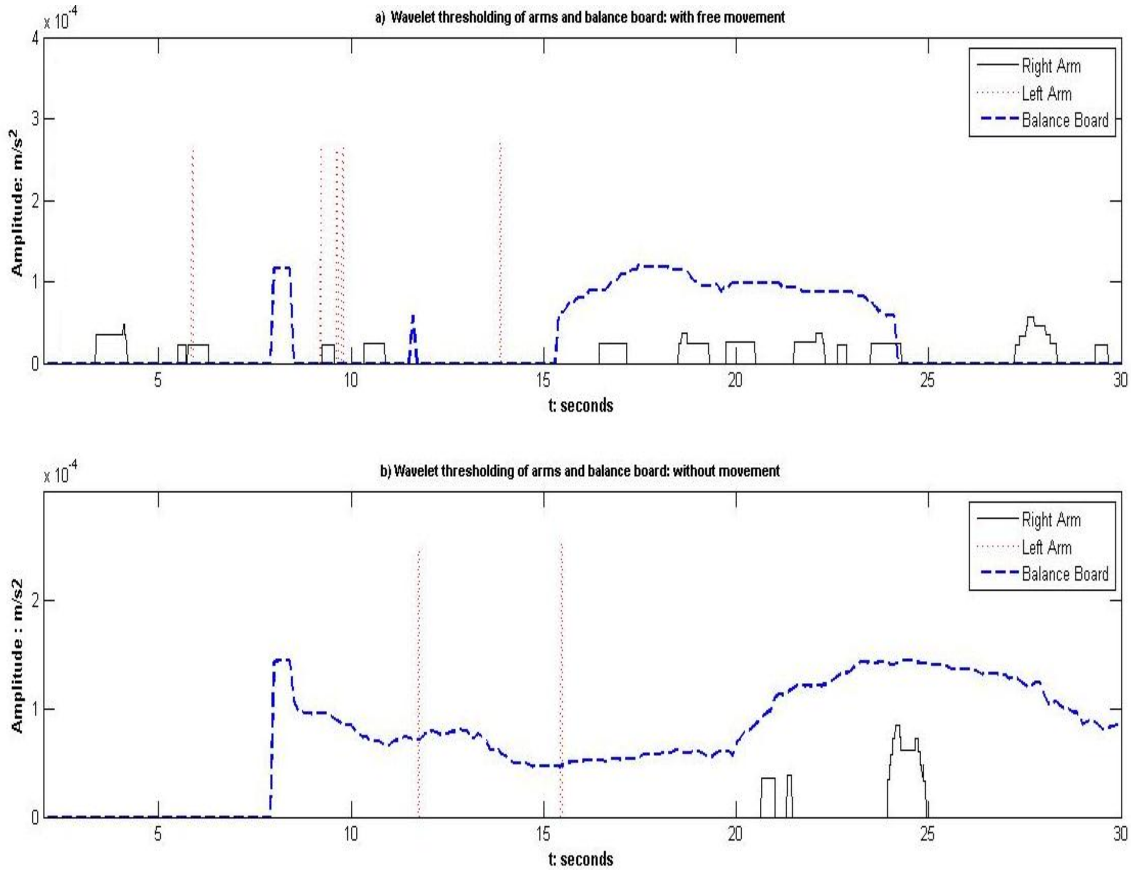


Figure 28. a) Integral threshold of arms and balance board with free arm movement and b) Integral threshold of arms and balance board with without arm movements from subject 1

Analysis of the results of arm movements from Table 3 shows that the dominant arm has a greater area and amplitude and effect than the non-dominant arm during both limited and free arm movements. This means maintenance and recovery of postural balance is improved with free arm movements when using dominant arm during the loss of balance and it has more of an effect than the non-dominant arm. From both Table 4 and Figure 28 appears that when arms are used in controlling the balance, the duration and amount of loss of balance is greatly lessened, which means the arms were used actively. Also, from both Figure 28 and Table 4 can be seen that whenever arms were used, the balance board was under more control and did not have a lot movements. From Figure 28 it appears that dominant arm moves more but with less amplitude in compare to non-dominant arm.

In total, for all four of the subjects the ratio between the areas of instability when arms were used versus when the arms were limited to no movement is about 74% and for dominant versus non-dominant arms is calculated to be about 55%. Therefore, these results provide further proof on the importance of arm movement in recovering loss of balance as well as the greater use of the dominant arm in this process. The above results were calculated based on the ratio of summation of area under the envelope thresholding for both limited arm movements and free arm movements for all subjects.

4.3 The Neural Network Algorithm

After using moving average filter and down sampling, which was shown in Sections 4-1 and 4-2, feature extraction must be performed. The accuracy of data classifiers using the statistical features is highly dependent on the number of classes present in the input data. With only two classes, such as in this project, each feature is able to provide correct classification.

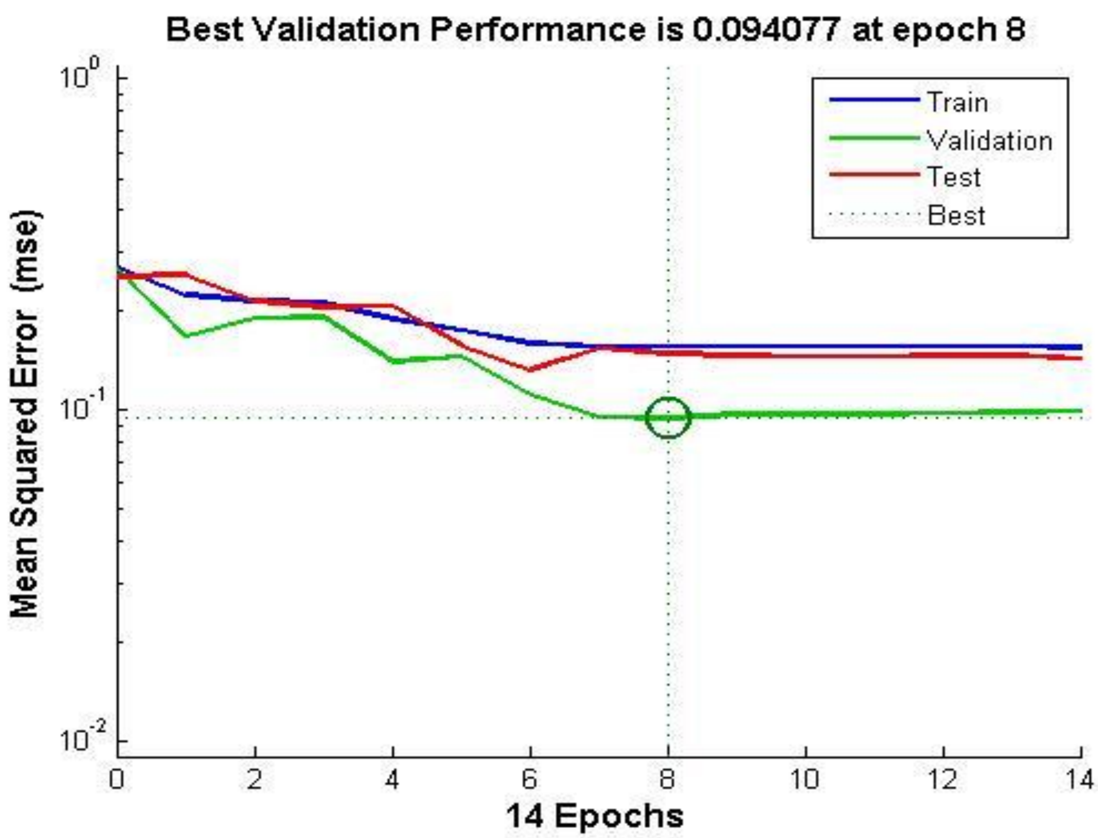
In this thesis, arm movement signals for all subjects were trained and arms without movements were tested in the same way in order to compare their performance. The statistical features (PSD, mean, variance, standard deviation and amplitude) made the network number one which is shown with net1 and the axis features are the components of network two, net2.

4.3.1. The training results

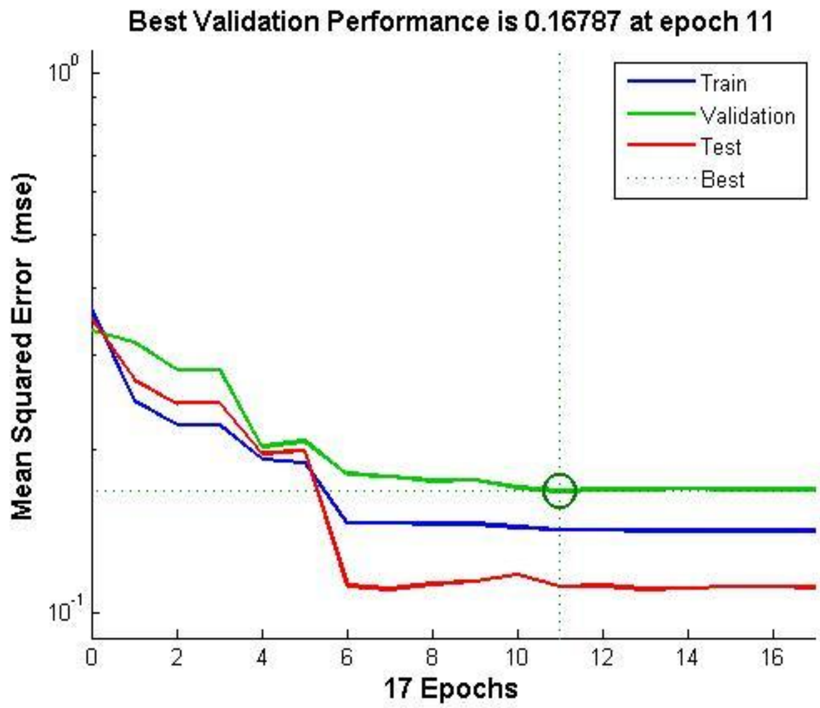
Table 5 and Figure 29 show the training process and performance of arm movements with 5 features as an input and 1 neuron in its output with choice of different hidden neurons in a hidden layer with balance board for one person out of four persons.

Table 5. The training performance of net1 for balance board

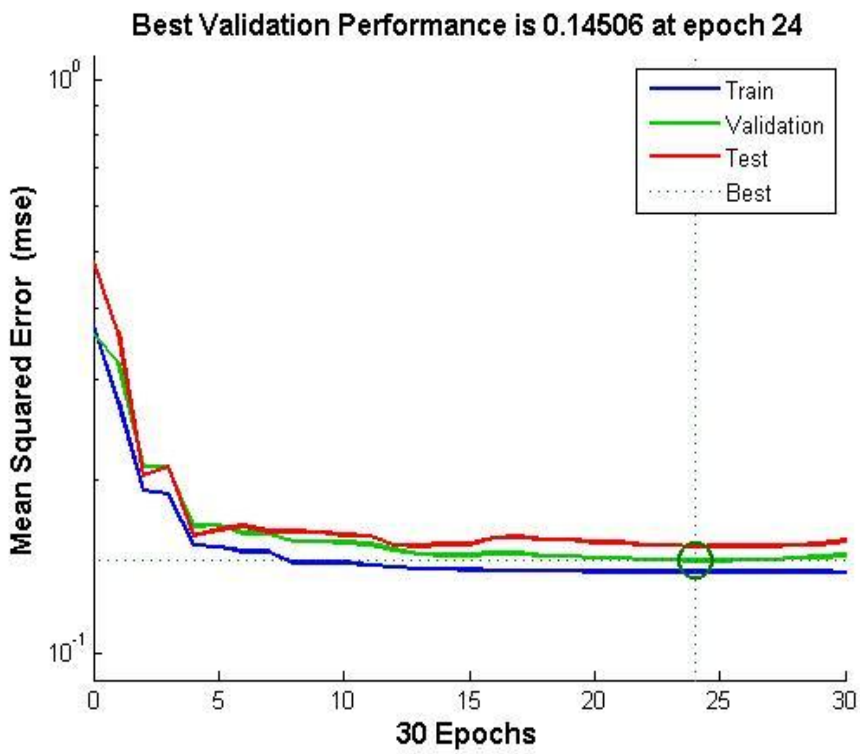
Network	Input layer	Output Layer	Hidden layer	Epoch	MSE
Net1-5	5	1	5	11	0.16787
Net1-10			10	8	0.094077
Net1-15			15	24	0.14506



a)



b)



c)

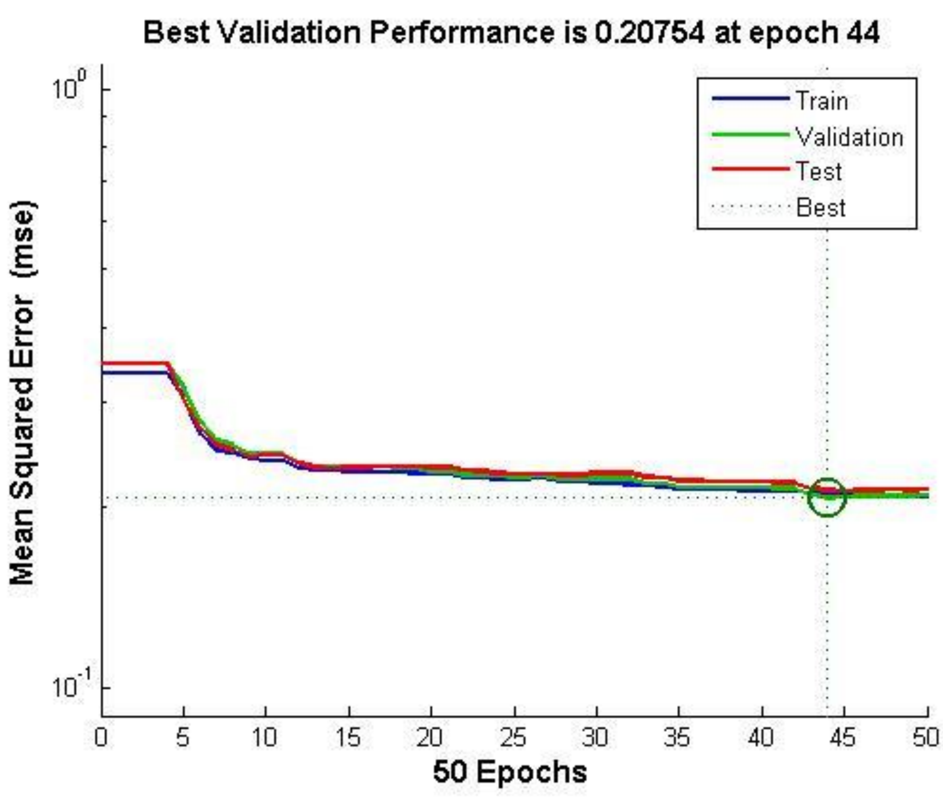
Figure 29. The training performance of a) Net1-5 b) Net1-10 c) Net1-15

It can be observed that the behaviour of the three networks in terms of training speed were different. The net1-10 trained with the least number of epochs and the net1-15 trained with the most epochs.

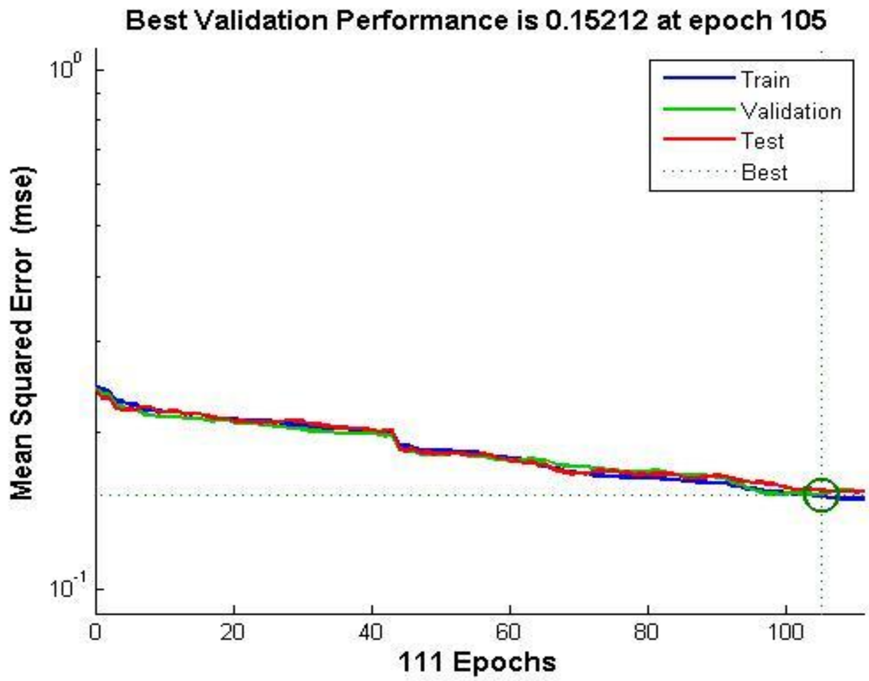
Table 6 and Figure 30 display the training process and performance of net2 with 9 inputs and 1 neuron in its output for varying numbers of neurons in the hidden layer.

Table 6. The training performance of net2 for balance board

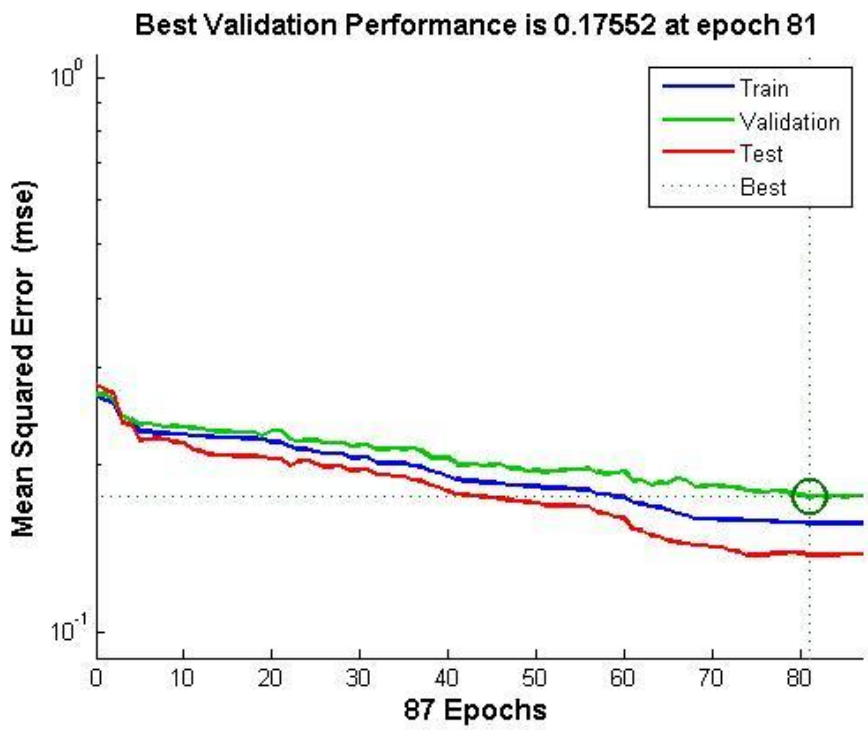
Network	Input layer	Output Layer	Hidden layer	Epoch	MSE
Net2-5	9	1	5	44	0.20754
Net2-10			10	90	0.08432
Net2-15			15	81	0.17552



a)



b)



c)

Figure 30 The training performance of a) Net1-5 b) Net1-10 c) Net1-15

It can be seen from the above results that net2-5 has the worst performance in spite of having the least epochs. In contrast, net2-10 has the best performance and the worst number of epochs.

Based on these results, the number of hidden neurons was chosen to be 10. Based on this number of neurons, the performance was shown in Table 7 for all subjects.

Table 7. The training performance of four subjects for balance board

network	Subject	Input Layer	Output Layer	Hidden Layer	Epoch	MSE
Net1	Subject 1	5	1	10	8	0.094077
	Subject 2				13	0.078312
	Subject 3				16	0.089313
	Subject 4				51	0.11133
Net2	All Subjects	9	1	10	90	0.08432

It can be observed that the behavior of four subjects and two networks in terms of the training speed and performance were different. Subject 1 trained with the least number of epochs and Subject 2 had the best performance under the same goal. On the other hand, Subject 4 had the worst performance with the most epochs in all subjects.

Table 8 reports on the performance of net1 and net2 using training signals of movements signal with features of 5 and 9 respectively.

Table 8. The training recognition rate of four subjects (with free movement)

Network	Subject	Input Layer	Output Layer	Hidden Layer	Recognition Rate %			Average Classification Rate %
					Right Arm	Left Arm	Balance Board	
Net1	Subject 1	5	1	10	94.9	91.6	78	88.1
	Subject 2				95	92.4	78.4	88.6
	Subject 3				96.5	95.2	83.5	91.7
	Subject 4				94.5	90.3	83.5	89.4
Net2	All Subjects	9	1	10	98.5	89.8	79.5	89.2

4.3.2. The testing results

By defining the output result of a Boolean array, one can evaluate the classification results and compute the recognition rate of the analytic results. This factor is equal to one when all real events in a specific subgroup are identified correctly.

Table 9 reports on the performance of net1 and net2 based on recognition rate using test signals of non-movements signal with features of 5 and 9 respectively.

Table 9. The testing recognition rate of four subjects (without movement)

Network	Subject	Input Layer	Output Layer	Hidden Layer	Recognition Rate %			Average Classification Rate %
					Right Arm	Left Arm	Balance Board	
Net1	Subject 1	5	1	10	90.8	89.7	79	86.5
	Subject 2				93.1	91.4	79	87.8
	Subject 3				94.1	89.3	87	90.1
	Subject 4				93.6	89.7	82.3	88.5
Net2	All Subjects	9	1	10	86.5	87.3	88.4	87.4

It shows that subject 3 in network 1 had the highest average classification rate of 90.1% and subject 1 had the lowest average classification rate of 86.5%. It also was decided that net1 had better classification rates than net2. So, it can be determined that the best architecture was net1 with 5 inputs and 10 neurons in hidden layer and 1 neuron in output layer.

The training behaviors of right arm, left arm, and balance board were different. As can be seen from Tables 6 and 9, in the same condition each arm and balance board had different performance. Right arm reached higher performance than left arm which means more effect on balance. When arm movement was constrained, balance board shows significant effect on maintaining balance. Also influence of arms in increasing balance and performance can be determined by the fewer epochs taken to reach balance.

In total, for all four of the subjects the ratio between the areas of instability when arms were used versus when the arms were limited to no movement is about 98.6% and for dominant versus non-dominant arms is calculated to be about 97%. Therefore, these results provide further proof on the importance of arm movement in recovering loss of balance as well as the greater use of the dominant arm in this process. The above numbers were calculated based on the ratio of summation of area under the envelope thresholding for both limited arm movements and free arm movements for all subjects.

4.4. Results and Discussion

As can be seen from the results, when subjects did not maintain balance on the balance board test, they did not use their arms and they have less arm movements. They also show that a lower magnitude of dominant arm movements is going along with minor reaching on a balance board test which means both arms must have a good coordination to each other to maintain the balance. These results confirm the concept of cancellation of body pointing movements' perturbations by upper arm motion which was mentioned in chapter 1by Pozzo et al. and Tee et al.[15, 16].

In summary, this chapter presented the results of the analysis of arm movements during maintenance of postural balance on balance board test. Arm movements were analyzed during unstable regions. This chapter also examines the role of dominant arm movements for balance maintenance and recovery. The results from balance region detection algorithm, the wavelet transform algorithm, and the neural network classification show that all algorithms have the same results about arms effect on the controlling balance. All these algorithms have illustrated that with limited arm movements, Subject 1 had the least difference between dominant and non-dominant arm movements and Subject 4 had the greatest one. On the other hand, in free arm movement, Subject 2 had the greatest difference between dominant and non-dominant arm movements and Subject 1 had the least difference between dominant and non-dominant arm movements. In both balance region detection algorithm and neural network, the effect of arm movements more obvious than the wavelet transform with the ratio of 98%. On the other hand, the neural network has the biggest ratio of dominant arm versus non-dominant with 98%. For comparing balance region detection algorithm and the wavelet transform, the wavelet transform detect the dominant effect more than other algorithm. But, the balance region detection has better result for detection arm movements in instability conditions. The difference between area is based on using a different methods of threshholding as well as different used methods, but the final result and conclusion are the same.

Chapter 5: General Discussion

There are lots of literature documents describes arm movements, reaching reactions and balance recovery [1, 9, 10, 14, 15] but few of them such as Milosevic [1] paid attention to arm movement strategies during dynamic balance and balance without any support. So, to cover this gap, this study was done.

Arm movements and their role in dynamic postural balance were presented in this study. The findings from balance test suggest that the arms play an important role in the improvement of balance and maintenance and recovery of postural balance with free arm movements. The analysis of the arm movements and balance board data examines the dynamics during balancing, segmented into the regions of stable balance and balance recovery, as well as the specific function of the dominant and non-dominant arms. The balance test results confirms the mentioned concept of importance of arms for reaching external supports or for supporting of impact in preparation of a possible fall, and movements that mentioned in chapter 1 [1, 9, 14, 15]. These results suggest that maintenance of postural balance and preventing falls can be developed by analytic and training of arm movements. Moreover, by using both arms in a harmonizing way, better balance will be achieved.

The results of balance test shows that the mean of non-dominant arm is greater than dominant arm, but in contrast dominant arm has the greater variance than non-dominant arm. These findings propose the variable and effectiveness of dominant arm by controlling the more dynamic parameters during balance versus static characteristics of non-dominant arm [1].

These findings are very important, since they provide support for a model of dynamic arm dominance that can be useful to the task of dynamic balance maintenance. They support the recent studies of human balance strategies such as reference 12.

By comparing the results, it can be seen that by maintaining lower amount of arm movements during stable periods of balance, the balance board test has the poorer results. In contrast, there is an active balancing with more use of arms and having better balance. So, it is more efficient for maintenance of dynamic postural balance.

As a summary, from all these results, the importance of arm movements in balance can be found and they have unique roles during balance recovery periods. The active strategy seems to be the main strategy during dynamic balancing tasks. My study provides successful evidence of the impacts of arm movements and their effects on dynamic balance. One of the limitations of this study is that the role and play of other body parts such as knees is not assumed. As another one, the subject's characteristics such as weight and height were not used.

A future study can be done with more subjects. Also, because the balance control is a complex skill and different sensory systems such as visual and vestibular affect it; it is a good idea to combine them with arms to recognize the effect of all human sensors. Other research can be done to compare the gender of subjects and evaluate the duration of arm movements for maintaining balance in them. Finding age effect on the balance can be evaluated as another research in the future.

Chapter 6: Conclusion

Loss of balance must be better understood as it relates to aging. This will help to access and protect people that are more likely to suffer from injuries due to falls. In this project, the responses due to perturbations on a balance apparatus were examined. Since the signal characteristics change so much from individual to individual, it is so difficult to form specific parameters such as amplitude, signal energy and bandwidth to classify unstable states. So, three algorithms balance region detection, the wavelet transform, and the neural networks were describe to make sure that the hypothesises are proven and correct. It was proven that balance region detection segmented unstable parts of the signal and effects of arm movements by definition of envelope that amplified the areas of instability. This component was further thresholded to better separate and finds the areas where movement occurred.

It was demonstrated that unstable sections of the signal corresponded to actual movement that were represented in the high frequency component of the wavelet transform. Experiments with the wavelet transform enabled the development of signal processing algorithms to segment periods of instability based on the acceleration vector obtained by an accelerometer on a balance board. This component was further thresholded to better isolate the areas where movement occurred. An adaptive method for choosing the best threshold was also presented.

A neural network classification was also developed to segment the signals in two classes: stable and unstable parts, which form the entire signal. The selected features were suitable for diagnosis of the unstable parts and enhanced the efficiency, simplicity and recognition rate of the neural network. The best performance of this network was for subject 3 with 90.1% in network 1 with 5 inputs and 10 hidden neurons.

Based on the results and experiences, it can be claimed that arm movements are important in dynamic balance maintenance. Firstly, by calculating the area under the derivative and integrated signal, the amount and duration of the activity can be found. This amount confirmed the importance of arms especially the dominant arm. Secondly, by observing algorithm results, it appears that with starting the balance board movements, both the dominant and non-dominant arm start to move, which is different in limited arm movement and free arm movement. These findings are useful for preventing falls with combining by training programs and provided clinical tools.

Publications

1. Manifar S, and McConville K, “Application of an Optimization Algorithm with Neuro-Fuzzy Parameter Generation for Master-slave Systems with a Classical Controller “, Journal of Artificial Intelligence for Engineering Design, Analysis and Manufacturing (AIEDAM), submitted, 2012

2. Shafiee M, Manifar S, Milosovic M, and McConville K,” Arm Movement Effect on Balance”, Accepted for presentation on 34th Annual International IEEE, EMBS Conference, San Diego, USA, Aug 27- Sept 1, 2012
    - In this paper, based on “balance region detection” algorithm which is the first described algorithm, I analyzed the arm movements by using Matlab. The results of this paper were mentioned in the thesis before.

3. Manifar S, Milosovic M, and McConville K,” Using Neural network for Arm Movements effects in Response to Posture Instability”, in preparation for International Journal of Adaptive Control and Signal Processing

4. Manifar S, Milosovic M, and McConville K,” Characterized arm movements in Response to human balance with neural Network”, in preparation for 2012 IEEE International Workshop on Genomic Signal Processing and Statistics, Washington, DC, USA, Dec 2, 2012 - Dec 4, 2012

5. Manifar S, Milosovic M, and McConville K,” Arm Movements effects in Response to Posture Instability based on Wavelet Analysis” , in preparation for the 38th IEEE International Conference on Acoustics, Speech, and Signal Processing, Vancouver, Canada, May 26, 2013 - May 30, 2013

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