

Ubiquitous Biofeedback Multimedia Systems

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Abstract

Human wellbeing, in a large component, relies on the harmony between the body and the mind. Unfortunately, we often miss or ignore important signals from our bodies, and sometimes this can negatively impact our health. Therefore, the use of intelligent systems that grasp such signals and convey them in an intuitive manner to our minds can result in great health benefits. In this Thesis, we introduce a family of multimedia technologies and techniques aimed at realizing such systems. We call them: Ubiquitous Biofeedback Multimedia Systems.

Although the notion of clinical biofeedback has been around for years, we introduce the concept of Ubiquitous Biofeedback where the biofeedback operation is given geographical and temporal ubiquity attributes. A Ubiquitous Biofeedback reference model is introduced in the Thesis to provide an abstract structural representation of the various components at play in a typical non-clinical biofeedback environment.

Two systems that implement the reference model's components are presented. These systems implement the concept of Ubiquitous Biofeedback through the introduction of innovative stress management methods. An important component of these systems guides users through a relaxation routine. Therefore, a mathematical model is developed in the goal of personalizing the relaxation process. Its objective is to suggest relaxation techniques to a user during a stressful episode based on her or his preferences, history of what worked well and appropriateness for the context.

The mental stress monitoring mechanism built into the Ubiquitous Biofeedback systems presented in this Thesis relies on the measurement of Heart Rate Variability (HRV). Therefore, HRV based methods for tracking mental stress accumulation and acute manifestations during long term monitoring have been devised. Also, since HRV signals can be plagued by artifacts, several algorithms are contributed to the effort of correcting such occurrences.

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List of Acronyms

ANS: Autonomous (or Autonomic) Nervous System
AV: Atrioventricular
BSG: Biofeedback Serious Game
CCB: Color Coded Bar
CSV: Comma Separated Values
DMT: Detrended Matched Template
ECG: Electrocardiography
EEG: Electroencephalography
EIBI: Expected Inter Beat Interval
EMG: Electromyography
FPDR: False Positive Detection Rate
FRF: Fundamental Respiration Frequency
GSR: Galvanic Skin Response
HF: High Frequency
HR: Heart Rate
HRV: Heart Rate Variability
IPFM: Integral Pulse Frequency Modulation
IR: Impulse Rejection
LF: Low Frequency
MA: Moving Average
MT: Matched Template
NVR: Normal Values Range
PAC: Premature Atrial Contraction
PNS: Parasympathetic Nervous System
PRA: Personalized Relaxation Assistant
PSD: Power Spectral Density
PVC: Premature Ventricular Contraction
PWIR: Pattern Windowed Impulse Rejection
RMSE: Root Mean Square Error
SA: Sinoatrial
SDNN: Standard Deviation between NN Intervals (Standard Deviation of HRV Signal)
OSC: Office Stress Check
OT: Original Template
SM: Stress Monitoring
SNS: Sympathetic Nervous System
ST: Simple Thresholding (HRV filtering method); System Training (OSC stage)
TPDR: True Positive Detection Rate
U-Biofeedback: Ubiquitous Biofeedback
UE: User Education
VLF: Very Low Frequency
WIR: Windowed Impulse Rejection

1 Introduction

1.1 Background

The metaphorical structural foundation of human wellbeing is supported by two pillars: the body and mind, and is based on two fundamental researches: human physiology and psychology, as shown in Figure 1.1. The word ‘Biofeedback’ was not coined until 1969, but the concept has been known for thousands of years in the form of meditation and various yoga techniques. For example, yogis have been consciously controlling their Autonomic Nervous System (ANS) (such as slowing their heart rate or increasing their body temperature) by observing their body’s performance. It is believed that the basis of biofeedback research was established in the 1930’s when progressive relaxation techniques [1] and autogenic training [2] were introduced. These techniques involve a daily practice that lasts for a certain time interval (for example 15 minutes) during which the practitioner repeats a set of visualizations and releases tension in the muscles to induce a state of relaxation. Such practices, supplemented with information relating to the mind and body (collected by electronic sensors), would later form the foundation for biofeedback [2].

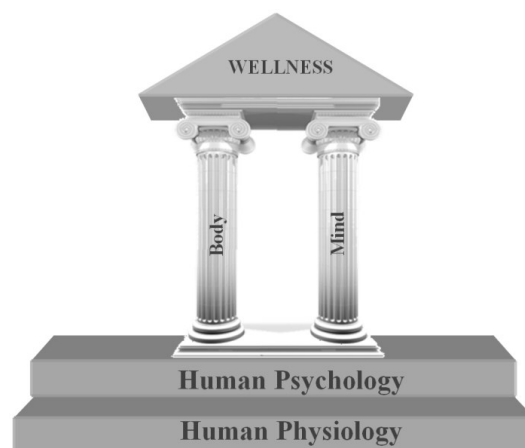


Fig. 1.1 Body-Mind Coordination

The term biofeedback was introduced at the first annual meeting of the Biofeedback Research Society (1969) as the acquisition of biological feedback through electrical instrumentation [3]. This era was marked by the development of a variety of biofeedback techniques (such as temperature biofeedback, EMG biofeedback, EEG biofeedback, and galvanic skin response) [4]. For instance, Miller and colleagues conducted a series of experiments on animals in order to determine whether the ANS could be volitionally controlled [5]. They demonstrated, through a series of articles, that responses such as blood pressure, blood flow, cardiac functioning and intestinal activity could to some extent be voluntarily managed. This led to other researchers demonstrating the same results on human beings. The works of Basmanjian [6] and Kamiya [7] are good examples of early human biofeedback experiments.

Biofeedback evolved from a research field into a clinical practice and eventually the term clinical biofeedback was coined [8]. Clinical biofeedback is defined by [8] as a type of operant conditioning whereby, with the help of a trained therapist, an individual can learn to control specific physiological functions by changing the thoughts and perceptions that produce them. Changing the mind state of the individual requires that several physiological parameters be electrically measured and presented in a comprehensible way. Today, clinical biofeedback is a well-recognized tool for self-regulation and stress relief. According to the Mayo clinic (one of the largest integrated medical centers in the world), biofeedback is a complementary and alternative medicine technique for treating more than 100 illnesses [9]. In contrast with clinical biofeedback that requires clinical setup and a coach to facilitate the subject's awareness of their physiological functions, we formalize the concept of Ubiquitous Biofeedback (U-Biofeedback), a reference model for systems that utilize software tools to provide continuous and long term management of physiological processes. Such systems are typically part of the user environment or worn on the subject's body. They do not require the

user to attend clinical sessions in order to benefit from biofeedback techniques. Moreover, U-Biofeedback systems can implement automated response techniques that guide individuals through a procedure aimed at controlling their physiological parameters.

The biofeedback research, from an engineering perspective, comprises the design, development, and testing of smart and precise instruments that measure physiological activities such as brainwaves, heart functions, breathing, muscle activities and skin temperature, and generate an appropriate feedback response. However, in this Thesis, we envision biofeedback systems that provide multimedia contents to trigger the user's mind, which eventually tunes the physiological parameters to optimize the body's performance. Such multimedia responses can come in the form of meditation or breathing instructional videos, games, music, relaxing imagery, etc...The biofeedback system should be able to detect, for instance, when a user is suffering extreme stress and present her or him with appropriate multimedia contents to drive the stress relief process.

Humanistic psychology emphasizes the unity of body and mind. Biofeedback takes this emphasis to a completely new dimension to create a mind-body medicine. The mind-body relationship can be formulated as follows: "Every change in the physiological state is accompanied by an appropriate change in the mental-emotional state, conscious or unconscious, and conversely, every change in the mental-emotional state, conscious or unconscious, is accompanied by an appropriate change in the physiological state" [10]. This concept is demonstrated in Figure 1.2.

Biofeedback is a closed loop feedback system in which information taken from the human body is translated into a language perceivable by any of the human senses (see Figure 1.2). The loop begins with the human body, which is connected to a biomedical sensor(s). The sensor reads the body's energy and converts it to an electric signal (after being conditioned – such as filtered or amplified). The electrical signal is then interpreted and converted to a

recognizable stimulus and then relayed back to the individual through one of the five senses. Once the biofeedback information is consumed by the human brain, a change in the mind state will occur, which stimulates a change in the human physiological state, and the cycle starts again. A high level of body-mind synchronization strengthens and builds harmony within the individual and eventually results in a higher level of wellbeing.

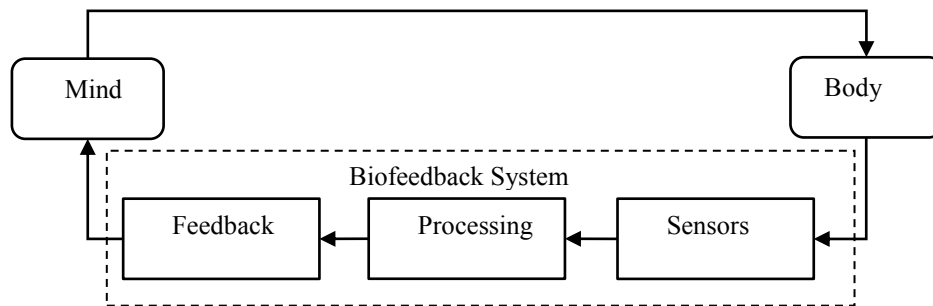


Fig. 1.2 The Biofeedback Loop (Body-Mind Loop).

1.2 Motivation

Classically, biofeedback exercises take place in a clinic under the supervision of a doctor or therapist. Nonetheless, in recent years, many works have challenged this classical notion by enabling such exercises from various non-clinical settings (e.g. home, work, car...). These systems are therefore aimed at achieving geographical biofeedback ubiquity. The studies presented in [11, 12, 13, 91, 92, 93, 97] fall under this umbrella. Nonetheless, to the best of our knowledge, no attempts have been made to formalize the concept of non-clinical biofeedback into a reference model. Such model should provide an abstract structural representation of the various components at play in a typical non-clinical biofeedback application. Note that these applications operate mostly independently from a clinician and interface directly to the user. Therefore, specific adjustments and additions are required to accommodate for the latter concept. Consequently, the formalization of the reference model

provides a standardization of the various components involved and the goal and scope of such systems. One of the principle objectives of this Thesis is to present this reference model.

Also, this model focuses on the concept of temporal biofeedback ubiquity. To the best of our knowledge, biofeedback exercises in most existing works are performed during time bounded sessions. A user of such systems commits her or his entire concentration to the exercise. Nonetheless, we advocate the principle of continuous monitoring of physiological data. The users go about their day while the system operates in the background. The biofeedback system becomes visible to the user in two situations:

- User prompts the system for physiological or psychological status
- System informs the user of a key physiological or psychological event and offers guidance in response (if needed)

1.3 Problem Statement

We would like to explore various methods in assisting individuals to achieve a higher level of wellbeing. To do this, we will conceptualize non-intrusive autonomous devices that drive this process using U-Biofeedback systems. Although all the methods that will be explored in this work fall under the general concept of U-Biofeedback, we will investigate various directions stemming from the latter notion. Nonetheless, the general goal of achieving a higher level of wellbeing will remain the underlying theme for all studied methods.

1.4 Contributions

In this Thesis, we will formalize the notion of U-Biofeedback and introduce a reference model for systems that comply with such concept. Moreover, additional contributions are presented in this Thesis. They generally belong to two categories:

- **U-Biofeedback methods:** These are methods that we have devised in order to enable the development of U-Biofeedback systems. They constitute contributions to the field of Ubiquitous Biofeedback and bio-signal processing.
- **U-Biofeedback systems:** These are systems that implement the U-Biofeedback reference model presented in this Thesis. Although they all have a similar scope and goal, they tackle the problem of enabling a higher level of wellbeing through biofeedback techniques from different angles.

The following are U-Biofeedback related methods that we have developed:

- Mathematical model to personalize the relaxation process in the context of U-Biofeedback mental stress management systems
- Acute mental stress detection algorithm for long term stress monitoring
- Mental stress accumulation monitoring method for long term stress management
- Filtering methods to remove and correct artifacts in Heart Rate Variability (HRV) signals (such signals are used in the analysis of mental stress).

The following are contributions that showcase the strength of the proposed reference model from several perspectives:

- Design of a U-Biofeedback Stress Management system for office employees
- Conceptualization of the notion of Biofeedback Serious Gaming in the context of U-Biofeedback systems
- Design of a Personalized Relaxation Assistant that improves the quality of the U-Biofeedback experience

Figure 1.3 provides a summary of the contributions of this Thesis.

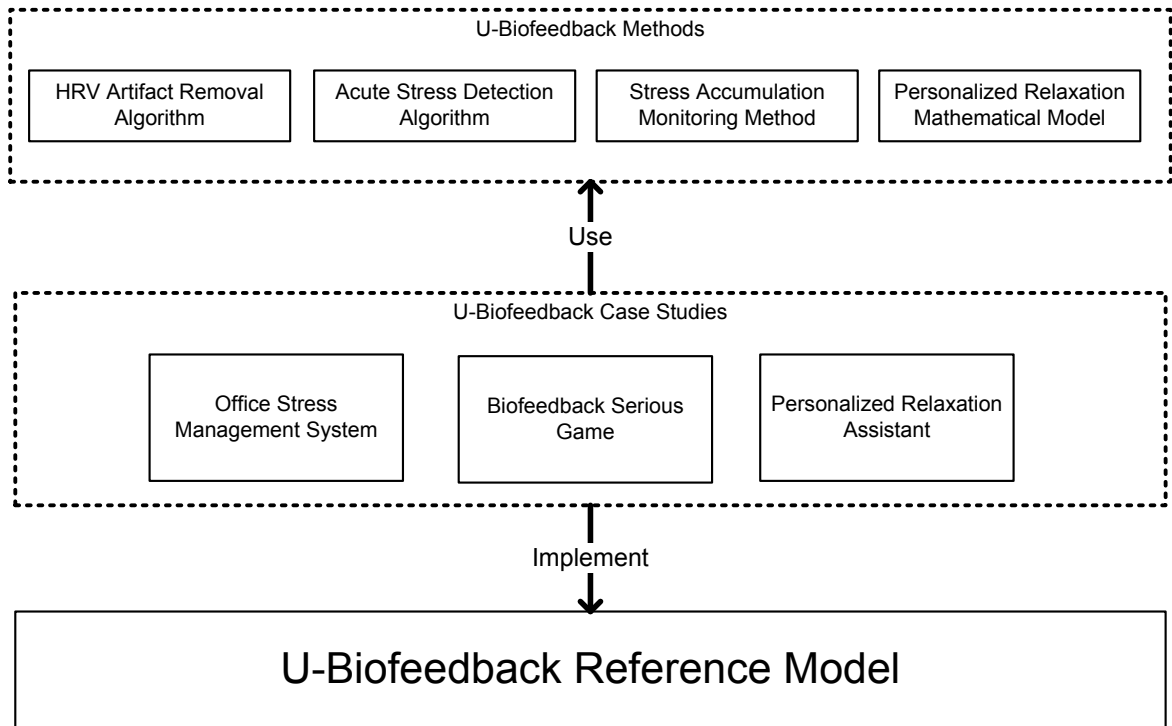


Fig. 1.3 Summary of Contributions

1.5 Scholarly Achievements

In the process of completing this work, the following publications have been submitted, accepted or published:

- Journal Papers:
 1. H. Al Osman, M. Eid, A. El Saddik, “U-Biofeedback: a multimedia-based reference model for ubiquitous biofeedback systems,” *Multimedia Tools and Applications*, July 2013. doi: [10.1007/s11042-013-1590-x]
 2. H. Al Osman, M. Eid and A. El Saddik, “A Windowed Impulse Rejection Filter for HRV Artifact Correction,” *IEEE transaction of Instrumentation and Measurements* (submitted)
 3. H. Al Osman, H. Dong, A. El Saddik, “Ubiquitous Biofeedback Serious Games,” *IEEE transactions on Human Machine Systems* (submitted)

4. B. Hafidh, H. Al Osman, A. Karime, J.M. Alja'am, A. El Saddik, "SmartPads: a plug-N-play configurable tangible user interface," *Multimedia Tools and Applications*, April 2013. doi: [10.1007/s11042-013-1459-z]
- Conference Papers:
 1. H. Al Osman, M. Eid. A. El Saddik, "A Windowed Impulse Rejection filter for HRV artifact detection," *Medical Measurements and Applications Proceedings (MeMeA)*, 2013 IEEE International Symposium on , pp.6-11, 4-5 May 2013
 2. M. Eid, H. Al Osman, A. El Saddik, "A mathematical model for personalized relaxation for stress management," *Medical Measurements and Applications Proceedings (MeMeA)*, 2013 IEEE International Symposium on , pp.201-206, 4-5 May 2013
 3. S. Hamdan, H. Al Osman, M. Eid, A. El Saddik, "A biofeedback system for sleep management," *Robotic and Sensors Environments (ROSE)*, 2012 IEEE International Symposium on , pp.133-137, 16-18 Nov. 2012
 4. M.F. Alhamid, M. Rawashdeh, H. Al Osman, A. El Saddik, "Leveraging biosignal and collaborative filtering for context-aware recommendation," *Proceedings of the 1st ACM international workshop on Multimedia indexing and information retrieval for healthcare*. ACM, 2013.

1.6 Thesis Organization

The Thesis is organized as follows:

- Chapter 2 provides the background and related works for the various topics tackled in this work,

- Chapter 3 discusses our Ubiquitous Biofeedback reference model along with its various components,
- Chapter 4 introduces the methods we devised to enable the monitoring of stress over prolonged periods of time,
- Chapter 5 presents three case studies, the first two introduce U-Biofeedback systems intended for stress management and the third describes a Personalized Relaxation Assistant application,
- Chapter 6 describes our Heart Rate Variability artifact detection and correction algorithms, and
- Chapter 7 provides a conclusion and an outlook on future works.

2 Background and Related Works

2.1 Types of Biofeedback Systems

Traditionally biofeedback systems have been classified as stationary versus mobile, wired versus wireless, analog versus digital, and binary versus proportional. For instance, some devices are small and portable that can be implanted onto the human body or be held in the hand, while others involve large instrumentation in a wall unit. Wired devices use a wired medium (such as copper wires or fiber optic cables) to communicate the biofeedback information to the computing system whereas wireless devices use the air interface as the communication medium (such as Bluetooth, infra-red, and Zigbee technologies). Analog devices generate analog signals whereas digital devices generate digitized information. Finally, binary devices provide on/off information about a particular physiological parameter whereas proportional devices reveals the amount of changes occurring for a particular physiological parameter [14].

The generally accepted classification is that biofeedback devices fall into two categories: binary and proportional [14]. A binary device informs the individual only whether he or she is controlling a specific physiological function or parameter. For example, a biofeedback device aimed at correcting the body posture would measure the neck curvature and a light would go on when a threshold is surpassed (unhealthy body position), and off when the curvature is less than the threshold (a safe body stand). On the other hand, proportional biofeedback provides the amount of change in a particular physiological attribute. For instance, a biofeedback device would measure the heart rate and display that information to the user via a gauge or a digital display. Because it provides more information to the user,

proportional biofeedback is thought to be more effective in terms of coaching users on how to control their physiological parameters.

2.2 Biofeedback Applications

Biofeedback has been researched extensively to facilitate treatment for a wide variety of illnesses and regenerative therapies such as migraine in both adults and children [15], cardiovascular disorders, hypertension, anxiety and duodenal ulcers, and in many cases the results obtained have been notably positive [16]. Furthermore, several researches have proposed that respiratory biofeedback training has assisted patients who suffer stutters [17], alleviated panic attacks [18], asthmatic conditions [19], treated hyperventilation syndrome, sleep apnea [20], as well as posttraumatic stress disorder [21]. Furthermore, biofeedback can complement the use of medication in pain management [22].

Biofeedback may also be used to control the biological responses that are associated with health problems, such as chronically tense muscles due to injuries or accidents, asthma, high blood pressure, and cardiac arrhythmias [22]. Some experiments even demonstrated the effectiveness of biofeedback in controlling autonomic body functions [23]. For examples, researchers in [23] studied 33 subjects, all females aging from 17 to 25, and divided them into two groups: one group was told verbally to decrease their heart rate while running on a treadmill and being monitored on an Electrocardiography (ECG) machine, the other group was told to decrease their heart rate but also were shown the ECG signal as a form of biofeedback. The results showed that participants trained with ECG biofeedback information showed a great degree of control of their heart rate compared to those who were trained with only verbal instructions. (For more information on ECG signals, refer to Section 2.5.)

2.3 *Ubiquitous Biofeedback*

Before we present some existing Ubiquitous Biofeedback (U-Biofeedback) systems, we must clarify the similarities and differences between such systems and wearable health monitoring technologies (as the distinction is seldom drawn in many existing works).

In fact, U-Biofeedback can claim its ancestry from wearable health monitoring systems. These systems constitute an amalgamation of several technologies that have seen immense advancements in the past few decades. The advancements include the miniaturization of microcontrollers, the development of advanced sensors and wireless transceivers and the improvement of battery technologies. In addition, the ubiquitousness of mobile and non-mobile computing devices has made the implementation of such systems more practical. Both types of systems must operate outside of a clinical or hospital setting. Therefore, typically, they rely on wearable sensors to measure biological processes.

Usually, a U-Biofeedback system measures one or more of the user's physiological parameters, analyses the collected data and relays it back to her or him in an intuitive manner. Therefore, the principle consumer of such information is the user. This is done in the goal of enhancing the user's physiological or psychological status (e.g. stress management applications), improving her or his performance at executing specific tasks (e.g. fitness and exercise optimization applications) or alleviating specific symptoms of a disorder (e.g. migraine pain relief applications). The long term goal of a biofeedback system is to train users to positively alter their physiological or psychological state and thus improve their wellbeing. Conversely, wearable health monitoring systems are in charge of measuring and storing information pertaining to the health of the monitored individual. The goal in many cases is diagnostic (capturing biological signals to diagnose or rule out illnesses). Also, such systems can be connected through communication networks to health care providers in order

to relay critical messages if the health of a monitored patient deteriorates. In many cases, the main consumer of the collected biological information in wearable health monitoring systems is the health care provider rather than the user (although the user can also sometimes access this information). Farella et al present an interesting Wireless Body Area Sensor Network (WBSAN) solution and demonstrate its efficacy for applications that detect human posture using a set of strategically placed accelerometers [94]. References [95] and [96] describe frameworks for remote monitoring of patients using wearable sensors. Figure 2.1 depicts the conceptual contrast between wearable health monitoring and U-Biofeedback systems. Figure 2.1A presents a typical wearable health monitoring system where multiple sensors attached to the human body relay their information to a local processing node (e.g. mobile phone). The local processing node in turn relays some or all of the collected data to a remote medical server through various communication means. Several parties might consume the information received by the medical server such as physicians, medical researchers and emergency service providers. Figure 2.1B shows a U-Biofeedback system where the main consumer of the data collected by the biological sensors is the user. Nonetheless, the remaining infrastructure typically associated with wearable health monitoring systems is optionally included.

U-Biofeedback systems must exhibit geographical ubiquity or both geographical and temporal ubiquity. These two terms were introduced and described in Chapter 1. The next Section will describe such systems.

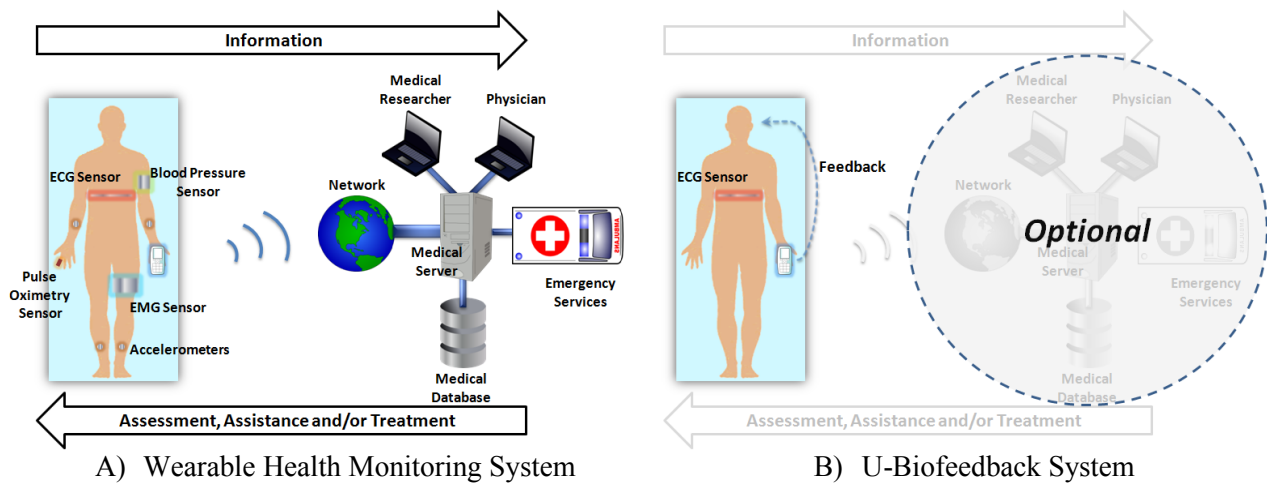


Fig. 2.1 Wearable Health Monitoring vs. U-Biofeedback Systems

2.3.1 U-Biofeedback with Geographical Ubiquity

An example of a U-Biofeedback system used to alleviate specific symptoms of a disorder is introduced by Chiari et al [91]. They propose an audio-biofeedback system for balance improvement intended for individuals experiencing imbalance symptoms [91]. Such condition can be caused by vestibular disorders or deterioration of the central nervous system circuitry [91], among others. The system converts 2D horizontal trunk acceleration into a stereo sound whose frequency, level, and left/right balance is modulated to convey the acceleration information. Similarly, Franco et al use the inertial sensors of a smartphone to estimate 3D triangulation of the trunk and provide auditory feedback to help the user improve her or his balance [13].

Conversely, U-Biofeedback systems can be used to improve specific physiological or psychological processes, such as better management of mental stress. To this end, Liu et al introduce a wearable respiratory biofeedback system intended for respiratory training in order to reduce feelings of stress or anxiety [12]. Moreover, the work described in [11] presents a biofeedback system that focuses on alleviating emotions of sadness and anxiety. The system uses an EEG sensor to collect and analyse information about the user's mood and

recommends appropriate music to reduce negative emotions. The user can observe the EEG feedback on a mobile platform as they listen to the recommended song. Other commercial biofeedback stress management solutions have been introduced. For instance, Heart Wizard presents products to track a subject's stress level (stress monitor) and to direct the subject through relaxation exercises (stress sweeper) [38]. Several other commercial products also claim to provide biofeedback based stress relief, nonetheless, in many cases, to the best of our knowledge, the scientific basis for these systems has not been presented in peer reviewed publications nor the validity of the claims has ever been independently verified.

In terms of using U-Biofeedback systems to improve performance during the execution of a task, Munroa et al present a textile knee sleeve device that provides auditory feedback on knee flexion [92]. The device is intended for athletes involved in sports involving jump-landing tasks. The feedback assists athletes in performing correct landing movements during landing training in order to avoid common injuries associated with abrupt deceleration such as anterior cruciate ligament ruptures. Moreover, [93] proposes an ear-lead ECG based sensor to monitor individuals during exercising and provide auditory feedback regarding potentially hazardous increases in the heart rate.

2.3.2 U-Biofeedback with Geographical and Temporal Ubiquity

Very few works present both geographical and temporal ubiquity as described in Chapter 1. Such systems should be easily deployable in various settings and must support prolonged monitoring. The work presented in [97] satisfies these requirements. It introduces a Galvanic Skin Response (GSR) based biofeedback system that continuously measures mental stress levels. GSR sensors measure the conductivity of the skin, a property that is known to reflect mental stress status [97]. Relatedly, [98] presents a wrist sensor that also makes use of GSR measurements to detect elevated stress situations.

2.4 *Stress Management Biofeedback Systems*

All of the biofeedback applications presented in this work are specialized in mental stress management. Therefore we present in this Section a brief introduction to the topic.

Stress has been the topic of numerous research endeavours, yet investigators still have to agree on a well-established definition for this concept [24]. In general, stress is an innate response to an environmental threat or psychological distress that triggers chemical and hormonal reactions in the body [25]. Elliot and Eisdorfer provide a classification of stressors based on duration and course. It defines five categories of stress [26]:

- Acute time-limited stressors involve temporary periods of nervousness brought upon through various exercises such as public speaking or mentally challenging problems. Such stressful stimulus can be typically instigated in a controlled manner in a laboratory setting in order to monitor various physiological effects.
- Brief naturalistic stressors are ones that occur naturally in a person's environment. Typical examples include an academic examination or a job interview.
- Stressful event sequences are related to traumatic events that might negatively impact a person over a prolonged period of time. The loss of a loved one for instance is an example of such stress.
- Chronic stressors alter a person's identity or social role. Such stressors are characteristic by their stability. That is, the person is completely unaware when the challenge will end or acknowledges that it will never end. Stress triggered by a life changing disability or illness falls under this category.
- Distant stressors are generated by past distressing events that continue to negatively affect the immune system because of long-lasting cognitive and emotional effects [27]. Examples of such stressors include child abuse and war trauma.

The American Institute for Stress lists 50 common signs and symptoms of stress ranging from headaches to heart palpitations [28]. Perhaps the difficulty with defining stress is exasperated by its subjective nature; it is indeed a phenomenon that differs for each individual [28]. There are various disorders that have been linked to stress. Heart attacks [29], depression [30], immune system disturbances [24], migraine [31] and vertigo attacks [32] are just few examples of such disorders. Creating a complete list of stress related ailments would be a very exhaustive endeavour due to its sheer size. Nonetheless, that highlights the importance of studying stress and exploring methods to effectively reduce its potentially harmful effects on our wellbeing.

Perhaps the most efficient stress management biofeedback system is already built into our bodies. For instance, we can often sense tension during stressful periods. It is the body's natural response. In fact, listening carefully to our bodies can offer us a plethora of information regarding our mental and physical state. Nonetheless, enrolling the help of electronic sensors' based biofeedback systems allows for the detection of subtle and rapidly changing signs of stress that can sometimes go unnoticed without such assistance. Also, we have a natural tendency sometimes to ignore signs of stress as we are preoccupied with life's challenges. Unfortunately, our psychological wellbeing occasionally slips down the priorities list.

One of the earliest electronic biofeedback systems employed for psychotherapy is introduced in [33]. The aim is to reduce tension headaches through a biofeedback supported relaxation technique. EEG sensors are used to measure the alpha waves which are more pronounced during wakeful relaxation. Auditory feedback is used to indicate the level of alpha waves and thus directs patients to increase relaxation. The same authors later developed a system based on multiple sensory feedbacks (galvanic skin response and skin temperature) [34]. Eisdorfer demonstrates the effectiveness of biofeedback-aided relaxation in comparison

to traditional relaxation methods [35]. His study makes use of a GSR biofeedback device from Thought Technology Ltd. [36] to measure stress level and of the Benson relaxation technique [37] for stress relief.

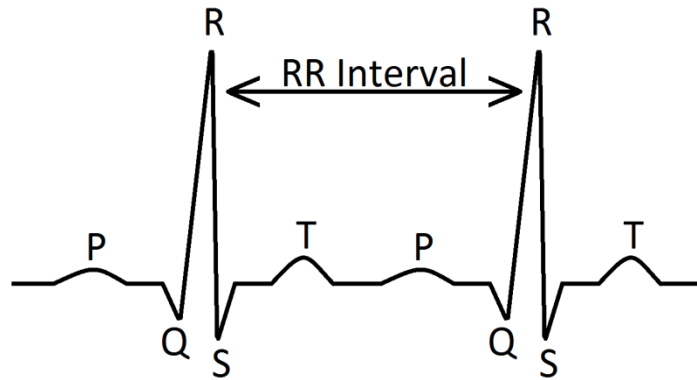


Fig. 2.2 Typical ECG Signal of a Healthy Heart

2.5 Heart Rate Variability and Stress

There exists many ways to measure mental stress using physiological information. Typically, the following methods are employed:

- Electroencephalography (EEG): measurement of the electrical activity along the scalp
- Skin Conductivity: measurement of the electrical conductivity of the skin
- Electrocardiography (ECG): measurement of the electrical activity of the heart
- Respiration Rate: measurement of the number of breaths per minute
- Electromyography (EMG): electrical activity of the skeletal muscles

Due to the abundance of ECG sensors customized for long term monitoring and their relative low cost, we have made use of ECG based methods in the analysis of mental stress. Moreover, a study of mental stress during driving tasks has shown that ECG based methods

are more accurate in terms of stress estimation compared to respiration and EMG based techniques [42].

In this work, we focus on a well-known approach to detecting stress from an ECG signal that makes use of Heart Rate Variability (HRV). HRV refers to changes in the time intervals between successive heart beats. The usefulness of such measurement was first demonstrated in [40] when the authors discovered that a decrease in HRV was associated with fetal distress. But most importantly, HRV properties tend to reflect the level of activation of the ANS components. The ANS is an important part of the nervous system that non-voluntarily acts as a controller for all the organs of the body, including the heart. Two branches of the ANS collaborate to regulate the body organs: the Sympathetic Nervous System (SNS) and the Parasympathetic Nervous System (PNS). The former stimulates the organ's functioning while the latter inhibits it. Together, they achieve the balance needed for an efficient organ functioning.

The idea of assessing HRV parameters in order to derive conclusions regarding the mental state of individuals has been the subject of many papers. For example, Cook and Song make use of HRV measure to examine the psychophysiological effects of mental workload in single-task and dual-task human-computer interaction [41]. Several other papers focused on the effectiveness of HRV analysis to monitor mental stress in individuals [42, 43, 44, 45, 46].

When it comes to HRV parameters, numerous time and frequency domain measurements have been used to extract useful information from an HRV signal. Note that an HRV signal represents the series of intervals between heart beats, or what is referred to as R-peaks (see Figure 2.2). (On an ECG graph, the peak of electrical activity, which coincides with the beating of the heart or more specifically the rapid depolarization of the left and right ventricles, is called the R-peak.) These intervals are commonly referred to as NN intervals (period between two normal heart beats). The study presented in [47] provides a

comprehensive list of such measurements. In the time domain, the standard deviation of an HRV signal is denoted as SDNN, which stands for Standard Deviation between NN intervals. SDNN is the most commonly measured parameter in the time domain. A decreased SDNN value has been associated with “lowered coping ability to various emotional/physical stressors” [48]. SDNN has also been used to assess acute stress levels for individuals [49]. Nonetheless, frequency domain based approaches for detecting stress received more attention from researchers [42, 43, 44, 45, 46] since specific frequency bands have been associated directly with components of the ANS [39]. These methods rely on the estimation of the power spectral density (PSD) of an HRV signal and retrieving specific frequency bands that are known to reflect the ANS status. Three major power bands have been generally recognized:

- Very Low Frequency (VLF): 0.003 to 0.04 Hz
- Low Frequency (LF): 0.04 to 0.15 Hz
- High Frequency (HF): 0.15 to 0.4 Hz

Two commonly accepted durations of measurement exist: long term (24 hours) and short term (3 to 5 minutes). The significance of the VLF band in short term measurements is still widely debated and mostly undefined [47]. While the topic of HRV is still somewhat of a controversial one in the medical community, there is general consensus about few important factors. For instance, the HF band has been closely associated with parasympathetic activity [39]. On the other hand, the LF band has been found to contain both sympathetic and parasympathetic components [39]. The LF/HF ratio has also been linked to the balance between sympathetic and parasympathetic nervous branches [39]. Numerous studies have found a significant decrease in HF component and an increase in the LF/HF ratio during stressful situations [39, 44, 45, 46, 50].

Detecting stress in individuals always relies on one essential factor: history (i.e. previous measurements and the mental state under which they were taken). It is almost impossible to take one physiological measurement, whether it is blood pressure, HRV, or skin conductance (all of which have been used to assess stress [42]) and conclude that a person is stressed. Let alone analysing how stressed is the person. All measurements are compared to previous ones. A straight forward approach would base the assessment on previous measurements collected during a period where the subject was not under a considerable amount of stress. The new measurement would then be compared to these previous ones and a conclusion would be inferred.

2.6 Heart Rate Variability Artifact Correction

Many types of cardiovascular arrhythmias can severely affect the integrity of an HRV signal. If the effect of such arrhythmias is not isolated, very little useful information can be yielded from the analysis of the signal. We will focus only on HRV signals collected from subjects that do not exhibit a history of heart disease. Usually the purpose of HRV data collected from such subjects is mostly to assess fatigue, mental stress level and wellbeing of the Autonomous Nervous System (ANS) in general. If we discount pathological arrhythmias, then an artifact in an HRV signal can mostly originate from two probable sources:

- Ectopic heartbeats: These are small variations in an otherwise normal cardiac rhythm. We will discuss their physiology in the next Section.
- Measurement noise: HRV signals are extracted from ECG sequences. Any degradation in the quality of the ECG signal or measurement interruption can be reflected as an artifact in the HRV record. Moreover, any ECG feature incorrectly identified as a QRS complex by the R-peak detection algorithm also produces an HRV artifact.

2.6.1 Physiology of Ectopic Beats

The heart's electrical activity originates at a cluster of cells called the sinoatrial (SA) node which act as the pacemaker of the heart system. From there, the electrical activity traverses the conductive heart tissue into the right and left atriums and hence causes them to contract. The same electrical pulse then passes through a compact component called the atrioventricular (AV) node to the right and left ventricles, causing them to contract as well. Any heart beat not generated from the SA node is regarded as an ectopic beat, a phenomenon that is mostly benign in nature.

Other than the SA node, the electrical pulse can be generated from three other locations: the atria, the AV node and the ventricles. Therefore, ectopic beats can be divided into two categories:

- Ventricular premature beats: these are contractions that result from electrical activity generated by the ventricles, and thus the name Premature Ventricular Contractions (PVCs).
- Supraventricular premature beats: these are contractions that result from electrical activity originating from the atria (called Premature Atrial Contractions (PACs)) or from the AV node.

2.6.2 Existing Artifacts Removal Techniques

Several artifact removal algorithms have been proposed. For instance, [51, 52] suggest the use of a simple thresholding technique where each HRV sample is compared to a predefined and static lower and upper bound. Any sample falling outside of this bound is considered erroneous. Nonetheless, such approach has limited efficiency on dynamic signals where the heart rate frequently changes. Many ectopic beats for instance produce HRV values that fall

well within the bounds of the normal heart rate range. (This became particularly apparent during our analysis of such method in Chapter 6.)

Another approach is proposed by [53] and [54] and makes use of a sliding average window filter. In [54], for each sample, the window consisting of the previous 30 seconds worth of data is averaged to produce a value upon which a lower and upper thresholds are based. The sample is considered to be an artifact if it falls outside the boundary of these thresholds. In [53], the algorithm involves the selection of a window size of $(2N+1)$ data points, averaging the N points on either side of the central point, excluding the central point if it lies a specific fraction outside of window average, then advancing to the next data point. Algorithms [53] and [54] are fairly similar, therefore, we have chosen to only further investigate algorithm [54] in Chapter 6.

Since all non-pathological HRV artifacts are manifested as impulses, [55] proposes an impulse rejection filter to identify erroneous samples. Alternatively, [56] bases the artifact detection method on the Integral Pulse Frequency Modulation (IPFM) model. The IPFM model has been suggested to simulate the work of the ANS in modulating the heart activity and thus the algorithm in [56] exploits this property to detect ectopic beats.

[57] provides a good discussion of simple filters used to detect pathological arrhythmias in HRV signals. Nonetheless, such work falls outside the scope of this work since it focuses on signals captured from healthy subjects.

In Chapter 6, we will investigate the effectiveness of all the aforementioned techniques (except the one presented in [57] since it falls beyond the scope of this work) in terms of their accuracy in detecting HRV artifacts. Also, we will look at the false positives produced by these methods. False positives refer to the erroneous identification of a correct data point as an artifact. Such false positives can critically affect the reliability of an HRV signal analysis. We will also present our own methods for artifact detection (Windowed Impulse Rejection

and Pattern Windowed Impulse Rejection) and analyse how they perform compared to the existing ones. We will also propose our solution for correcting HRV signals after all the artifacts are identified. The main component of signal correction is the interpolation of new samples to replace erroneous ones. We will discuss an interpolation method suggested in [55] and propose additional ones (linear interpolation and cubic interpolation). We will evaluate the accuracy of these techniques compared to the one presented in [55].

2.7 Relaxation Assistance

An ideal stress management system not only informs the user of stress level increase events, but also assists them in achieving relaxation. Traditional computer assisted relaxation applications rely on Biofeedback techniques similar to the one provided in [35]. In the latter, the relaxation level is measured, using a skin conductivity sensor. Feedback in the form of an audible tone, that decreases or increases according to the level of skin resistance, is in charge of informing the subject of her or his relaxation status.

Other creative approaches for relaxation have been explored. For instance a relaxation system which collects physiological information using a skin conductivity sensor and teaches users how to relax through gaming is introduced in [58]. Users are asked to play games where the degree of progress depends on the user's ability to relax. Furthermore, the authors in [59] demonstrated how music can change an individual's physiological state for the better by triggering their relaxation response. In this case, the heart rate of the user is encoded as musical data conveyed as pitch or tempo. This in effect indicates to the user her or his approximate heart rate. The use of music as a feedback method is intended to assist the user in the relaxation process and therefore reduces the state of emotional arousal.

An exploratory research project at Intel, named Mobile heart health, for mobile stress therapy on a smart phone platform is introduced in [60]. The project provides subjects with

just-in-time coaching that is triggered by physiological indicators to help them tune in to early signs of stress. The suggested therapies include breathing and physical relaxation exercises (the Body Scan), cognitive reappraisal prompts (the Mind Scan), and coaching for collaborative communication. Nonetheless, in this particular study, the only therapy tested was the breathing exercises.

2.8 *Biofeedback Serious Games*

Another focus of this work is the use of serious games in the context of biofeedback applications. We will therefore explore some of the related works pertaining to this subject.

Some of the most prominent healthcare oriented serious games are related to fitness. Such applications are aimed at promoting healthy habits by motivating players to perform exercises at various intensities. Typically, whether through the use of a tangible user interface or a camera, the user's movements are translated into game commands. Such types of applications are commonly referred to in the literature as exergames [61]. Hafidh et al discuss the development of a tangible user interface intended for such games [61]. In their study, the authors introduce several games that encourage kids to move around in order to solve puzzles. Kinect fitness on the other hand provides a bundle of exercising applications that run on the xbox platform and make use of the kinect camera to capture the player's activity [62]. The exercises supported include personal fitness training, various team sports and zumba exercises [62]. Although such applications are among the most popular health centered serious game, they do not support a biofeedback component.

Few works have made use of biofeedback systems in the context of gaming. Leahy et al present a biofeedback gaming scenario for teaching relaxation to patients with irritable bowel syndrome [63]. Electrodermal sensors are used to monitor changes in the level of stress. The aforementioned bio-signal is used as input to a game where progress is expressed in terms of

the stress level reduction. The feedback is presented in the form of animation rendered on the game interface. Bersak et al introduce the concept of “affective feedback” where a computer process becomes an intelligent participant in the biofeedback loop [64]. Therefore, a two way relationship is created between the player and the computer application. A change in the physiological state of the user affects the state of the application and vice versa. To prove their concept, the authors of [64] introduced a racing game controlled by a bio-signal collected from the players. The amount of relaxation is taken as a measure of success. Therefore, the player that relaxes the most wins the game. In this work, they also used electrodermal sensors to measure the level of calmness for each player.

Abstractly, biofeedback is targeted towards increasing the level of wellbeing for individuals [65]. Some games have been suggested to contain a biofeedback component, but they somewhat deviate from the aforementioned goal. They are basically aimed at augmenting the gaming experience through the use of bio-signals. Consequently, they replace or enrich the traditional controllers with physiological input collected by bio-sensors [66]. References [66] and [67] are good examples of such games. They focus mostly on the physiological augmentation of game controls rather on therapeutic objectives.

2.9 Conclusion

In this Chapter, we have introduced many concepts that we will refer to throughout this Thesis, such as biofeedback, stress management, electrocardiography (ECG), heart rate variability (HRV) and HRV artifacts. But most importantly, we have defined the term U-Biofeedback and compared it to wearable health monitoring technologies. We have also discussed several existing U-Biofeedback systems.

In contrast to existing systems, in this Thesis, we will develop U-Biofeedback systems that possess the following properties:

- Exhibit both geographical and temporal ubiquity. This means that such systems can be deployed in almost any setting and can run continuously. Most existing systems, such as [11, 12, 13, 91, 92, 93] focus on geographical ubiquity only.
- Define pre-set and customizable procedures to assist users achieve their goal (in terms of achieving a higher level of wellbeing). This is defined as the system's response to reduce the impact of unwanted situations (e.g. increase in the level of stress). To the best of our knowledge, none of the existing systems provide an extensive choice of response mechanism. Also, none of them allow for the personalization of the response mechanism.
- Keep track of the progress of the user in order capture positive or negative long term and short term trends. This is especially important since the eventual goal of biofeedback systems is to teach individuals to consciously reverse negative psychological or physiological processes. Therefore, an indicator of progress allows the user to observe her or his advancement towards this goal. According to our research, none of the U-Biofeedback systems we have examined support this feature.
- Use highly portable sensors in order to support the use of such systems in a multitude of settings and while performing various tasks. The systems presented in this Thesis rely on HRV analysis in order to discriminate situations of stress. To the best of our knowledge, all of the existing U-Biofeedback stress monitoring systems, such as [97, 98], use GSR measurements, which are susceptible to environmental temperature and humidity level changes [99].

Therefore, in this Thesis, we have developed a reference model for such systems. We have also developed and tested two systems that strictly implement the features of this reference model.

3 A Reference Model for U-Biofeedback Systems

Two branches of the biofeedback field can be defined: clinical biofeedback and U-Biofeedback (see Figure 3.1). In this Section, we formulate the concept of U-Biofeedback and draw the distinction between this technique and classical clinical biofeedback. Clinical biofeedback as the name suggests is performed under the supervision of a health practitioner, typically in a clinical setting. The subject is guided through exercises where she or he is made aware of key physiological parameters and assisted through various procedures to control them. These sessions are typically bound by time and the setting in which they are performed (typically a clinic). U-Biofeedback, on the other hand, is a continuous process that is neither bound by time nor setting. For instance, a U-Biofeedback system designed to monitor mental stress can be activated almost anytime and anywhere where the individual feels that her or his mental stress level tend to increase (e.g. work, classroom, car...). Many studies describing systems that fall under the umbrella of Ubiquitous Biofeedback have been published [11, 12, 13, 91, 92, 93, 97]. Most of these studies, as we have mentioned in Chapter 1, are more concerned with geographical ubiquity rather than temporal ubiquity. But, to the best of our knowledge, a reference model for such systems has not been defined. Therefore, this Thesis will introduce the Ubiquitous Biofeedback reference model, which describes our vision for such applications and standardises the main component that are habitually involved in such systems.

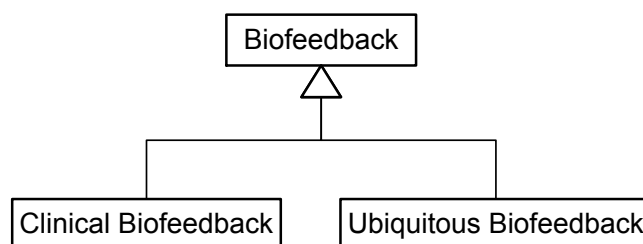


Fig. 3.1 Branches of the Biofeedback Field

3.1 Awareness Process

Biofeedback is like a horse-race track where the starting and finishing points are the same. As shown in Figure 3.2, the awareness process begins with the human body (physiology), which is connected to various Sensors that measure physiological parameters. The captured data is fed into the Signal Processor component which performs various signal conditioning activities and then forwards the processed information to the Signal Analyser. The Signal Analyser implements algorithms to analyse the collected data and compute the response strategy. The drawn conclusions are communicated back to the human mind through the feedback component (via one of the five senses). Finally, the mind stimulates the body and the cycle repeats.

All captured information is stored in a data repository for short and long term trend analysis. Furthermore, the collected data can be optionally communicated to a remote system for health monitoring or statistical analysis by interested parties.

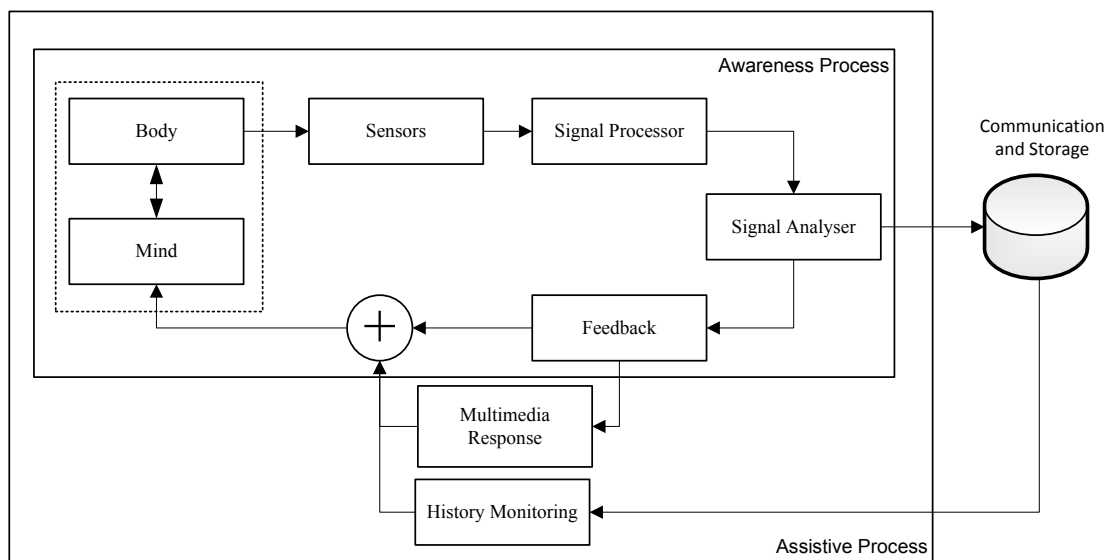


Fig. 3.2 U-Biofeedback Reference Model

3.1.1 U-Biofeedback Sensors

A sensor is an instrument that converts a physical phenomenon into an electrical signal. The types of sensors that can be used for U-Biofeedback applications are identical to the ones employed in health monitoring systems and are typically worn directly and noninvasively on the body. They can also be embedded into clothes, eyeglasses, belts, shoes or wristwatches [41]. These sensors are in charge of continuously performing measurements on features describing the physiological state or movement of a human body [41]. Alexandros and Nikolaos provide a good overview of wearable medical sensors [68].

3.1.2 Signal Processor

The Signal Processor component is responsible for performing different types of signal conditioning actions on the acquired sensory data. Examples of signal processing algorithms include, but are not limited to, signal filtration, amplification, multiplexing, isolation, and linearization methods. Signal filtration removes unwanted components from the signal that is being measured. Signal amplification, a very common task performed during signal conditioning, is used to increase the amplitude of the signal. Signal multiplexing is needed for measuring several signals with a single measuring device (for example when several biofeedback signals are read simultaneously into the biofeedback system). Finally, many biofeedback sensors have a nonlinear response to changes in the phenomenon being measured and thus should be corrected to a linear behaviour (known as linearization).

3.1.3 Signal Analyser

The Signal Analyser component has the distinct responsibility of making sense of the collected sensory information. It is thus in charge of analysing the physiological state of the individual being monitored. For instance, if a subject is being continuously examined for

elevated mental stress levels, the Signal Analyser would be poring over information reflecting the status of the user's ANS in order to assess the stress situation.

Signals collected by sensors are functions of time. A time domain signal expresses how its amplitude changes over time. Habitually, a time domain analysis of such signals can reveal an enormous amount of information regarding the state of a subject. For instance, to measure the heart rate from an ECG chart, a time domain examination of the signal is required. However, in some situations, frequency domain analysis renders valuable information that might be otherwise hard to uncover in a strict time domain investigation. Simply put, a frequency domain examination of a signal illustrates how often its amplitude changes over time. For example, many important Heart Rate Variability (HRV) parameters of an ECG signal can most effectively be measured in the frequency domain. Such parameters are important in assessing the level of fatigue and mental stress of an individual being monitored. (The topic of HRV will be later discussed in more details.) Sometimes researchers resort to time-frequency analysis where a comprehensive study of the signal is performed in both the time and frequency domains simultaneously [69].

For prolonged monitoring activities, a considerable amount of data is usually collected. Combing through the enormous amount of information can be a tedious task even for the fastest computing devices. Good care is usually taken to filter out unwanted records while data mining techniques can be employed to find important events [70].

3.1.4 Feedback

Feedback is the process by which a user is made aware of her or his physiological status. This is an essential part of the biofeedback loop where all collected and analysed information is relayed to the user. The ways in which the information is relayed are countless and can make use of conceivably any or a combination of the subject's senses. For instance, for a

simple application that makes a subject aware of her or his heart rate, the type of feedback can range from a simple interface showing the number of heartbeats per minute on a visual display to a complex multimedia system showing a 3D graphical representation of a heart beating with auditory effects.

3.2 Assistive Process

It is during the assistive process that the U-Biofeedback model diverts from the classical biofeedback process represented in Figure 1.2. During this process, the user is assisted in modulating her or his internal processes to achieve a higher level of wellbeing. This goes beyond the simple feedback reflecting physiological information and into helping the user adjust detrimental physiological or psychological situations. Also, this process is concerned with allowing the user to monitor short and long term progress achieved during the use of the U-Biofeedback system.

3.2.1 Multimedia Response

In order to provide external assistance to the mind in controlling the body, the biofeedback system extends the awareness model by proposing an assistive component: the Multimedia Response (as shown in Figure 3.2). The Multimedia Response component is accountable for aiding the user in manipulating her or his physiological or psychological parameters. For instance, in a stress management application, instead of simply informing users that they are stressed through a feedback module, the system attempts to guide them through relaxation exercises. These relaxation methods can be any of the traditional exercises traditionally associated with relaxation, such as meditation, progressive muscle relaxation or breathing. Other methods can include playing games, watching humorous videos and listening to slow music or peaceful sounds among many.

3.2.2 History Monitoring

The use of biofeedback tools usually takes place over a period of weeks or months. Therefore, a mechanism offering a historical view of psychological or physiological information measured directly or deduced from measurements over time is required.

For instance, if a U-Biofeedback system is used for stress management, a method that allows the user to review previously measured stress indicators with different levels of granularity can be of great benefit. Using a coarse grained historical review allows the user to examine which days, weeks or even months have been less (or more) stressful and therefore question what factors contributed to that situation. Analysing the source of stressors might enable the user to avoid or cope with certain stress inducing situations. A more granular assessment allows the user to evaluate which hours of the day are less stressful. Such functionality would likely manifest in the form of graphs expressing various physiological or psychological parameters with respect to time. Also, such form of historical monitoring enables the user to perform trend analysis to assess whether the monitored physiological function has improved over time.

3.3 Guidelines for U-Biofeedback Application Development

In order to realize U-Biofeedback systems that can be used over prolonged periods of time, while not restricting the user's activity or compromising her or his privacy, we propose the following guidelines for the design and development of such systems:

- The data acquisition devices should continuously capture physiological information without disturbing the daily life of the subject. The sensory devices should be light and small to minimize the discomfort they might cause to the wearer;

- The U-Biofeedback system should be able to perform in a completely autonomous way (have the ability to be fully automated);
- The U-Biofeedback system must perform over a long period of time (in the order of days, weeks, or months, rather than hours or minutes);
- The U-Biofeedback system must capture one or more physiological parameters that reflect the status of the body's performance; capturing more parameters can potentially increase the accuracy of the system;
- The U-Biofeedback system must ensure data confidentiality;
- The U-Biofeedback system must be able to log and store information for long periods of time (may utilize data compression/reduction techniques).

4 U-Biofeedback Methods

The focus of this Thesis will be on a particular subset of U-Biofeedback systems: Stress Management Applications. In order to realize the latter applications, we devise several methods (including a mathematical model and an algorithm) to process and analyse biologicals signals that reflect levels of mental stress or relaxation. These methods are discussed in details this Chapter.

Section 4.1, discusses the Sensor module (refer to the U-Biofeedback reference model) that we will use to collect the biological information necessary to support stress management activities. Section 4.2 presents the Signal Processor module (part of the U-Biofeedback reference model) that processes the biological signals received from the sensor in order to extract relevant features that reflect mental stress levels. These two modules will be used in all presented U-Biofeedback systems. Section 4.3 presents two mental stress monitoring methods:

- **Acute stress detection algorithm:** detects acute stress events on the monitored subject
- **Stress accumulation monitoring method:** keeps track of the amount of stress experienced by a subject over a period of time

Section 4.4 presents a personalized relaxation mathematical model that customizes the stress relaxation process responsible for stress diffusion to better suit the subject's preferences and needs.

All these methods are necessary to implement the U-Biofeedback systems that we introduce in Chapter 5.

4.1 *Sensor Module*

We used Zephyr Bioharness [71] to extract the relevant biological signals and prepare them for processing. To fulfill the requirements of the systems presented in Chapter 5, two biological signals are collected: ECG and Respiration. Also, the sensor's onboard 3D accelerometer is used to estimate the activity level. The ECG signal, as described in Chapter 2, summarizes the electrical activity of the heart; likewise the respiration signal indicates the breathing frequency. Both of these signals are expressed with respect to time. Zephyr Bioharness also produces a Vector Magnitude Unit (VMU) value out of the acceleration information. Acceleration VMU data has been used to estimate the activity level in numerous studies [81, 82, and 83]. ECG is collected using a single lead configuration with two electrodes attached to the chest using a chest strap. The signal is sampled at 1 kHz [84], which is above the 250 Hz minimum sampling rate required for HRV analysis [47]. The respiration signal is collected by measuring the size differential of the thoracic cavity to deduce inhaling and exhaling activities [84]. The respiration signal is sampled at 25 Hz and is considered accurate only under sedentary conditions [84]. The accelerometer is sampled at 100 Hz, but a VMU level is produced out of the average of the acceleration data at a rate of 1Hz [84].

4.2 *Signal Processor*

The Signal Processor is responsible for amplifying, sampling, filtering and extracting relevant information from a raw biological signal coming directly from a Sensor module. The module takes three inputs: ECG, respiration and VMU. It also produces HRV time domain parameters (Heart Rate and SDNN), HRV frequency domain parameters (LF, HF and LF/HF) and the Integrated VMU (IVMU) parameter (Figure 4.1). Heart Rate (HR) refers to the

number of R peaks per minute detected in an ECG signal (see Figure 2.2). SDNN, LF, LF/HF and HF were all described in Chapter 2. IMVU will be described in the subsequent Sections.

In order to calculate the frequency domain parameters, we need to estimate the signal's Power Spectral Density (PSD). The procedure for taking an ECG and respiration rate signals and producing the required parameters is performed in several steps as described below:

- Detect R peaks in the ECG record and calculate a list of RR intervals
- Resample the list of RR intervals at constant intervals in order to obtain an HRV signal (example shown in Figure 4.2)
- Correct any possible artifacts detected in the HRV signal (most commonly caused by an ectopic or premature heart beats) using the technique presented in Chapter 6
- Estimate the Power Spectral Density (PSD) of the HRV signal
- Calculate the time and Frequency domain HRV parameters

The particular sensor we used, Zephyr Bioharness, has a built in R peak detection algorithm, and therefore, the sensor directly supplies us with a list of timestamps corresponding to R peaks. This makes the calculation of the RR interval list a simple task. We resampled the RR interval at 4Hz before correcting any possible artifacts using the method described in Chapter 6. In order to estimate the PSD, we used Welch's method, which is an improvement over the raw Fourier transform technique as it reduces noise and variance in the estimated spectrum [85]. Nonetheless, it tends to reduce the frequency resolution. The method involves the segmentation of the time domain signal into overlapping windows (or segments) and calculating their averaged periodograms. For our particular application, we applied a hamming window to every segment and used a window size of 256 samples with 50% overlap between windows.

Now that we have obtained the PSD of the HRV signal, we are ready to extract the relevant frequency domain parameters (namely LF and HF). Nonetheless, since HRV is significantly affected by the modulation in the respiration rate [45, 86], it is crucial to take it into account for an accurate HRV analysis. Therefore, the respiration signal is processed through the following steps:

- Apply a low pass filter to the respiration rate signal to remove any inconsistent measurements and smooth out the signal
- Estimate the Fundamental Respiration Frequency (FRF) using the same method described in [86]

Using the FRF and the HRV PSD signal, we can extract the adjusted HF and LF parameters using the method presented in [86].

A basic activity monitoring mechanism is required to ensure that mental stress is not measured during periods of strenuous activity. This is motivated by two reasons:

- The accuracy of the Zephyr Bioharness sensor drops during increased activity, especially for respiration rate measurements [84].
- The sympathetic nervous system is excited during increased activity [88]. This is not due to an increase in the level of stress, but rather caused by the natural need for the heart, among other body organs, to be excited in order to support the increased movement. Therefore, such phenomenon might incorrectly be interpreted as a stressful event.

Therefore, the VMU signal inputted into the Signal Processor Module is processed through the following steps:

- Apply a low pass filter to the VMU signal to remove any inconsistent measurements and smooth out the signal

- Integrate the signal to obtain a single Integrated VMU (IVMU) value for the whole measurement period.

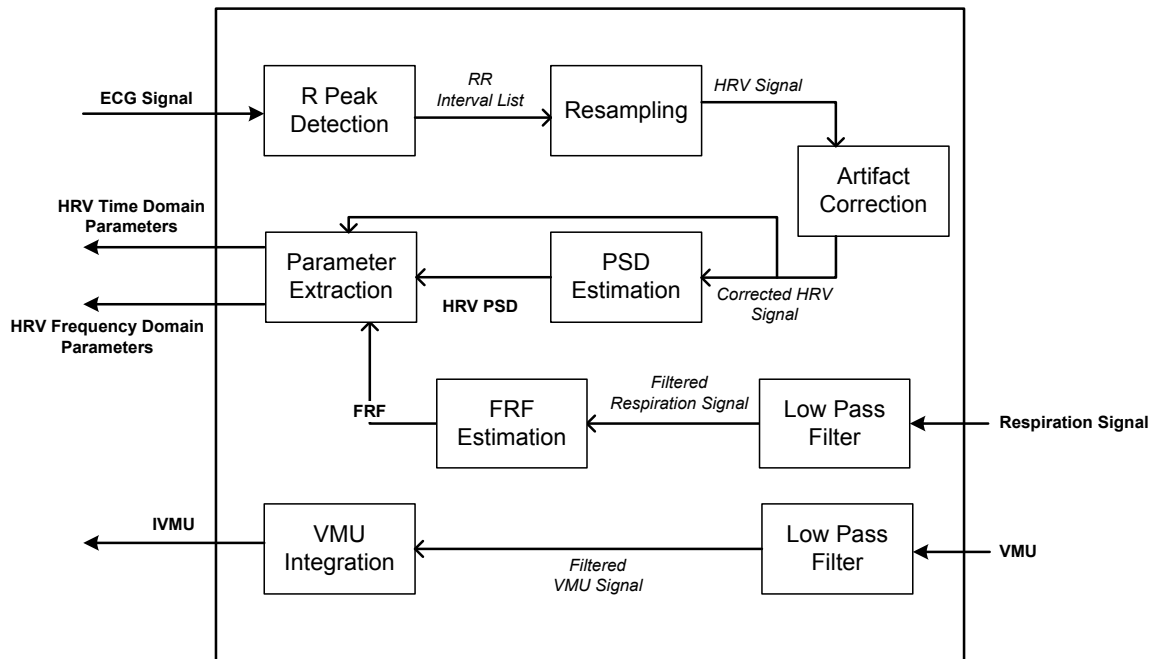


Fig. 4.1 Signal Processor

Two commonly accepted durations of HRV measurements exist: long term (24 hours) and short term (3 to 5 minutes). We conduct our analysis on 3 minutes worth of HRV data. The 3 minutes periods are overlapped to produce time and frequency domain outputs every 30 seconds after the initial 3 minutes period.

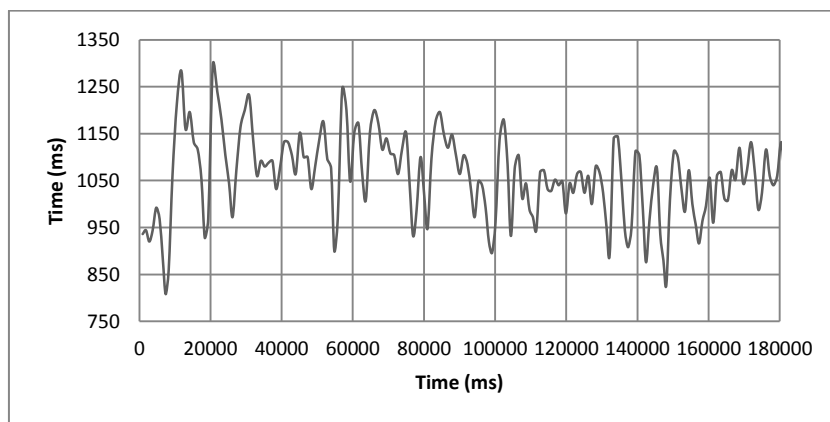


Fig. 4.2 Example of a Resampled HRV Signal

4.3 Stress Monitoring Methods

In order to monitor the mental stress levels experienced by an individual, we must first establish benchmark measurements. All subsequent measurements during monitoring activities will be compared to these benchmarks. The next Section details the benchmark collection procedure.

Before we proceed further, it is necessary to define two terms that will be used frequently in the next Sections of this Chapter:

- **Measurement:** refers to the value of a single parameter (e.g HR, SDNN, LF, HF, LF/HF or IVMU) calculated by the Signal Processor Module at a given time
- **Measurement set:** refers to the set composed of the values of all the parameters outputted by the Signal Processor Module at a given time

4.3.1 Benchmark Collection

Benchmarks are collected for each parameter produced by the Signal Processor. Once the benchmarks are established, stress monitoring activities can begin. In order to obtain these values, biological signal collection is performed over a period of time (minimum one hour for long term monitoring) where the mental stress level remains somewhat stable for the entire data acquisition period. Given two states, one of “no stress” and the other of “extreme stress”, benchmark collection should be performed during “low to moderate stress” status, which falls somewhat between the “no stress” state and the midway point between the two extremes. During the benchmark establishment phase, a user should engage in mundane tasks that require low to moderate amounts of concentration and are unlikely to significantly increase mental stress. The benchmark procurement activity produces a signal called $hp_{i[j]}$ for each HRV parameter, where i refers to one of the following parameters:

- | | |
|---------|----------|
| 1. HR | 4. LF |
| 2. SDNN | 5. LF/HF |
| 3. HF | 6. IVMU |

And j refers to the measurement set number, with $j=0$ denoting the first benchmark measurement set collected. We assume that these measurements, given that they are collected during almost the same stress status, follow a normal distribution, with μ_{HR} , μ_{SDNN} , μ_{HF} , μ_{LF} , $\mu_{LF/HF}$ and μ_{IVMU} as the median and σ_{HR} , σ_{SDNN} , σ_{HF} , σ_{LF} , $\sigma_{LF/HF}$ and σ_{IVMU} as the standard deviation for parameters HR, SDNN, HF, LF, LF/HF and IVMU respectively.

4.3.2 Acute Stress Detection Algorithm

To detect acute stress events, we calculate a Normal Values Range (NVR) for each parameter. This is done by applying the median filter on every $hp_i[j]$ signal to remove inconsistent measurements (that might have unusually been affected by noise or movement). The median filter is chosen for its capability to reject impulses in a signal, and therefore removing any abrupt changes that are very unlikely to be caused by sudden ANS shifts. This is achieved using Equation (4.1).

$$fp_i[j] = \text{median}(hp_i[j - \lceil w/2 \rceil], \dots, hp_i[j + \lceil w/2 \rceil]) \quad (4.1)$$

Where w is the window size of the median filter (can be adjusted by the operator) and $fp_i[j]$ is the filtered signal of the HRV parameter i . By default, w is set to 3.

Once the signal $fp_i[j]$ is produced for each parameter i , a default NVR_i is defined for each one of them as follows:

- If an increase in the value of the signal reflects stress (i.e. LF/HF and HR), then the NVR_i , by default, corresponds to the maximum of $fp_i[i]$.

- If a decrease in the value of the signal reflects stress (i.e. HF and SDNN), then the NVR_i , by default, corresponds to the minimum of $fp_i[i]$.

Table 4.1 Conditions for Preserving or Discarding $SA[n]$ Samples

Condition	Action
$IVMU[n] > (\alpha \times \sigma_{IVMU}) + \mu_{IVMU}$	This is an invalid measurement set and therefore should be discarded. The average activity level during the period of measurement n is too high to consider the measurement valid or corresponding to a level comparable to that of the benchmark.
$IVMU[n] \leq (\alpha \times \sigma_{IVMU}) + \mu_{IVMU}$	This is a valid measurement set and therefore should be preserved. The average activity level during the period of measurement n is within the threshold compared to the benchmark value.

Now that the NVR is established for each parameter, the monitoring activity can begin. Figure 4.10 summarizes the acute stress detection procedure. Every 30 seconds, a new measurement set (called $\Psi [n]$) is collected. $\Psi [n]$ is defined as the set $\{HR[n], SDNN[n], HF[n], LF[n], (LF/HF)[n], IVMU[n]\}$, where n refers to the measurement set number (with $n=0$ for the first measurement set collected during monitoring). A measurement set is valid only for a certain level of activity. Therefore, it is preserved or discarded according to the conditions presented in Table 4.1. Note that α (from Table 4.1) is a decimal number greater than 1.0 and can be set by the operator. When a certain percentage (denoted by τ) of valid measurement sets fall out of range for a preselected period of time (denoted by ϕ), then the person is judged to be experiencing acute stress. A measurement set is judged to be out of

range if at least one of the parameters being monitored falls outside of its NVR. By default, τ is set to 0.5, ϕ to 15 minutes and α to 2.0.

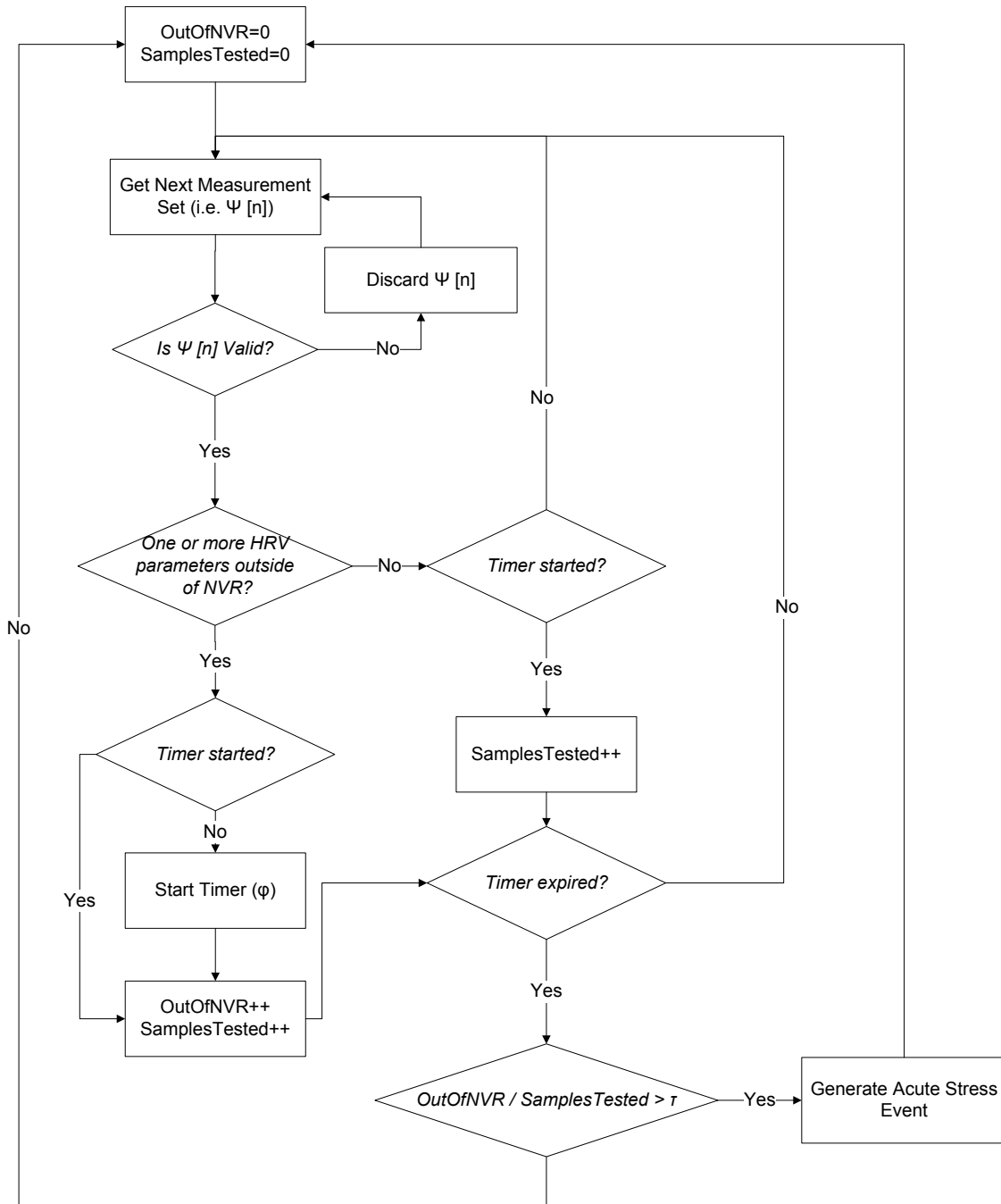


Fig. 4.3 Acute Stress Detection Algorithm

4.3.3 Stress Accumulation Monitoring Method

In order to keep tabs on stress accumulations, we model the evolution of stress level over time as a stochastic process or an indeterminate phenomenon. Therefore, an index for every subsequent measurement of HF and LF/HF is calculated using Equations (4.2) and (4.3).

$$HF_i[n] = \frac{100}{\sigma_{HF}} \left(\frac{HF[n]}{\mu_{HF}} - 1 \right) \quad (4.2)$$

$$(LF/HF)_i[n] = \frac{100}{\sigma_{LF/HF}} \left(\frac{\mu_{LF/HF}}{(LF/HF)[n]} - 1 \right) \quad (4.3)$$

$$f[n] = \frac{HF_i[n] + (LF/HF)_i[n]}{2} \quad (4.4)$$

Where $HF_i[n]$ and $(LF/HF)_i[n]$ are the HRV High Frequency and Low to High Frequency ratio indices associated with measurement n . The average of both of these indices is computed using Equation (4.4) to produce the Stress Index $f[n]$. Therefore, a value of $f[n]$ equal to zero refers to no change relative to the median of the benchmark measurements. A value of $f[n]$ greater than zero refers to an increase in relaxation level (compared to the benchmark median) proportional to the magnitude of $f[n]$. Similarly, a value of $f[n]$ smaller than zero signals an increase in stress level. Note that we based our stress accumulation model on only the HF and LF/HF HRV parameters, as they have been known to be the most reflective of mental stress [39, 44, 45, 46, 50]. Nonetheless, the stress index can be easily expanded to account for the remaining HRV parameters. Equation (4.5) is used to compute the Stress Accumulation (SA) over time.

$$SA[n] = (f * g)[n] = \sum_{m=0}^{n+k-2} f[m]g[n-m] \quad (4.5)$$

Where $SA[n]$ refers to the stress accumulation calculated after HRV measurement n and $(f * g)[n]$ is the convolution of $f[n]$ with a kernel function $g[n]$. The kernel dictates how the stress accumulation is modeled. The most basic kernel function is presented in Equation (4.6) where N is the length of $f[n]$. This kernel function permits all the values of $f[n]$ to be

averaged in order to produce a stress accumulation that equally takes all the previously accumulated $f[n]$ samples into account.

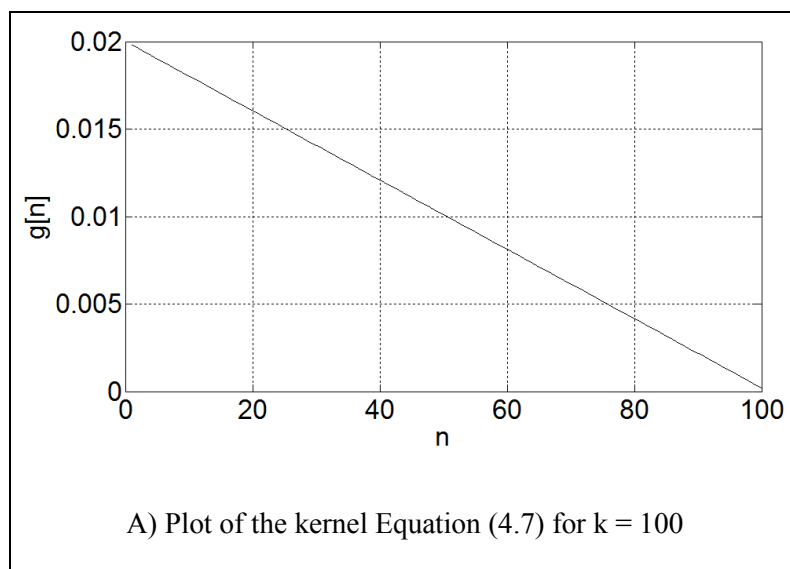
$$g[n] = \frac{1}{N-1} \quad (4.6)$$

Nonetheless, when it comes to experiencing mental stress, we likely attribute more significance to recent experiences. Therefore, we might want to use alternative kernel functions that place more weight on recent measurements and gradually less weight on previous ones. Two proposed kernel functions are presented in Equations (4.7) and (4.8) where k refers to the size of the kernel (i.e. how many past samples do we look at in the process of calculating $SA[n]$). Figure 4.4 shows the plot of these two kernels.

$$g[n] = \frac{2(k-n)}{k^2+k} \quad (4.7)$$

$$g[n] = \frac{e^{-\frac{\alpha(k-n)}{k}}}{\sum_{n=0}^{k-1} (e^{-\frac{\alpha(k-n)}{k}})} \quad (4.8)$$

Nevertheless, the $SA[n]$ values computed using Equation (4.5) are only considered valid for a certain level of activity. Therefore, they are preserved or discarded according to the conditions presented in Table 4.1.



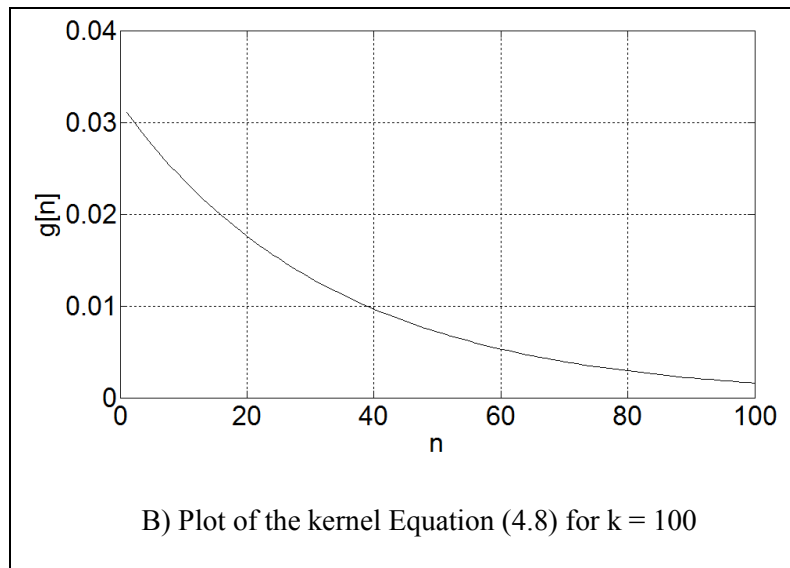


Fig. 4.4 Two Proposed Kernel Function for the Calculation of the Stress Accumulation

4.4 Personalized Relaxation Mathematical Model

The systems that will be presented in Chapter 5 shall recommend that the user engages in a relaxation process whenever acute stress events are detected. The response to stress differs from one individual to another depending on their personalities, cognitive style (characteristic thinking patterns), background and prior experiences, gender and ethnicity among many factors [77]. Also, to more effectively treat stress, the choice of relaxation technique should be “determined by the specific needs of individuals and the techniques that best suit those needs” [78].

We present a mathematical model that aims to personalize the relaxation process as the system learns what works better for a particular user. The objective of this model is to track the user’s reactions to various relaxation techniques by monitoring physiological responses and eventually determining what best matches the user’s needs.

Let X be the initial preferences for the relaxation techniques where each elements x_i of X belongs to the interval $[0, 10]$. This means that out of n relaxation techniques, each element of X corresponds to the preference allotted by the user to that particular technique, with 10

being the highest preference and 0 being the lowest one. Note that these weights might not be necessarily accurate as occasionally users might not be aware of what works best for them. Nonetheless, the user should be made aware that a preference of zero completely disqualifies a relaxation technique from being ever suggested.

$$X = [x_1 \quad x_2 \quad x_3 \quad \dots \quad x_n]^T \quad (4.9)$$

Let W be the Evolved Relaxation Preferences Matrix. These preferences will evolve as the relaxation process is run and data is collected regarding the efficiency of different techniques. Initially, W is equal to a scaled value of X . The scaling is performed by dividing each element of X by the sum of all the elements of that matrix. The values of W are updated to reflect how effective particular techniques were in the last relaxation iteration. Therefore, as W evolves, the relaxation procedure becomes more personalized according to the physiological feedback obtained from the user.

$$W = [w_1 \quad w_2 \quad w_3 \quad \dots \quad w_n]^T \quad (4.10)$$

Many relaxation techniques bear some similarities, whether in the kind of stimulus they provide (e.g. relaxing music and relaxing sounds) or the kind of activity they promote (e.g. deep breathing meditation and visualization meditation). α is called the correlation matrix (an $n \times n$ symmetric matrix) as it describes the relationship between any two defined relaxation techniques. Each element of α belongs to the interval $[0,1]$. For instance, napping and watching funny videos have no relationship and thus the correlation factor between the two is zero. On the other hand, listening to music or peaceful sounds are somewhat similar techniques as they both use auditory stimulus and therefore might have a correlation factor bigger than zero.

Additionally, we define the following parameters:

- Variable t represents the number of instances the relaxation process has been run.
- $p_i[t]$ represents the Performance Index of relaxation technique i at instance t . The value of $p_i[t]$ is based on the physiological responses after a relaxation technique is consumed. $p_i[t]$ is a real number that belongs to the interval $[-1,1]$.
- U is a matrix of size n and holds the unscaled value of W calculated using Equation (4.11). Calculating U takes into account the influence of the measured Performance Index of the last consumed relaxation technique i on the values of W , depending on their correlation with that relaxation technique.

$$u_j[t] = \begin{cases} x_j, & t = 1 \\ (\alpha_{i,j} \times p_i[t] \times w_j[t-1]) + w_j[t-1], & t > 1 \end{cases} \quad (4.11)$$

Equation (4.12) calculates the scaled value of W . Basically the scaling ensures that the sum of all elements of W is equal to 1.

$$w_j[t] = \frac{u_j[t]}{\sum_j^n u_j[t]} \quad (4.12)$$

Matrix O combines the actual preference W with the environmental factors matrix E . Matrix E holds elements that describe the appropriateness of each relaxation technique for different environmental settings. For instance, it would not be suitable or safe for a user to observe relaxing images while she or he is driving. Assuming that m environmental contexts are defined for the system (such as work, car, home, etc.), E would be an $m \times n$ matrix capturing the relationship between m environmental contexts and n relaxation techniques. Therefore, the following equation can be derived:

$$o_i(t) = e_{c(t),i} \times w_i[t] \quad (4.13)$$

Where $e_{c[t],i}$ represents the appropriateness of environmental context $c[t]$ at instance t for relaxation technique i . Therefore, we can define $F[i,t]$, called the personalization matrix and

calculated using Equation (4.15), as a probability mass function that can be used to randomly calculate an index between 1 and n . That index corresponds to the recommended relaxation technique.

$$s[t] = \sum_{i=0}^n o_i[t] \quad (4.14)$$

$$F[t] = \left(\frac{o_1[t]}{s}, \frac{o_2[t]}{s}, \frac{o_3[t]}{s}, \dots, \frac{o_n[t]}{s} \right) \quad (4.15)$$

5 U-Biofeedback Systems Case Studies

This Chapter presents three U-Biofeedback case studies. All of them focus on the concept of stress monitoring, management and relaxation. The first one introduces an application targeted for office employees and is intended to assist users in managing their stress levels. We call this application: Office Stress Check (OSC). The second case study introduces a mobile application intended for the same purpose, but this time, a gaming scenario is used to present the feedback to the user. We call this application: Botanical Nerves. The latter application belongs to a class of systems we refer to as Biofeedback Serious Games (BSGs). The third case study presents a Personalized Relaxation Application that improves on the relaxation assistance features of the systems presented in the first two case studies.

All applications will make use of HRV measurements to detect and analyse the mental stress situation that a user is experiencing (or even the quality of a relaxation technique that a user has consumed). We will therefore make use of the methods provided in Chapter 4 to monitor users' stress intensity and provide a personalized relaxation experience.

5.1 *Office Stress Check Case Study*

The OSC is intended for office employees who are interested in detecting acute stress manifestations. Not only would the OSC detect such stress events, but also would assist the user with a corrective action. This is achieved as follows (see Figure 5.1):

- Sensors, worn on the body of the user, relay relevant physiological information to a computing device. In this case, a Zephyr BioHarness sensor [71] worn on the torso communicates with the employee's work computer, tablet or mobile phone (Figure 5.2).

- At the computing device, a local program running the Signal Processor and Signal Analyser modules processes the received data and devises a Feedback and Multimedia Response
- The Feedback and Multimedia Response are conveyed back to the user through multimedia display devices

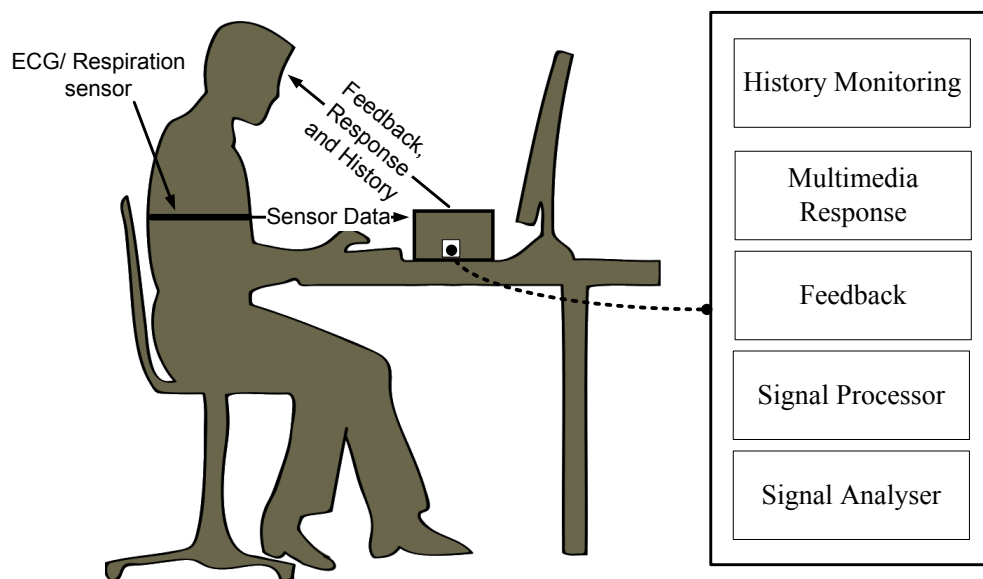


Fig. 5.1 OSC Stress Management Application

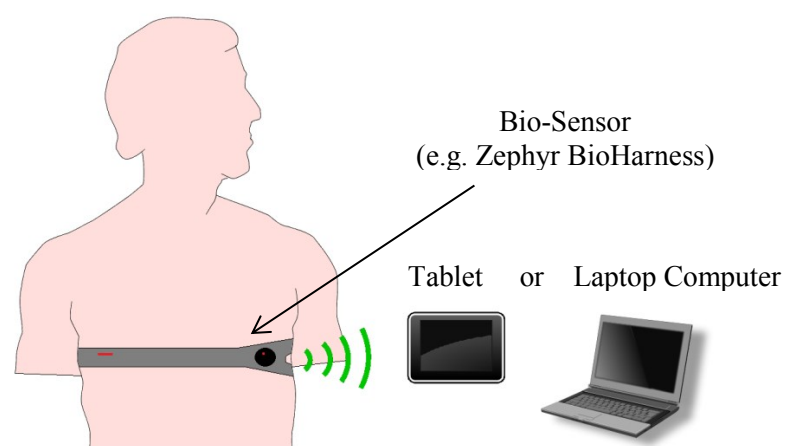


Fig. 5.2 HRV Monitoring Setup

5.1.1 Stages of Operation

OSC defines three stages of operation:

1. User Education
2. System Training
3. User Monitoring

The user must complete a stage before proceeding to the next one. The goal is to eventually reach the User Monitoring stage where the user's mental stress is being continuously examined by the application. The stages of operation are described in the next three Sections.

5.1.1.1 User Education Stage

The objective of a typical biofeedback application is to give subjects insight into the inner workings of their bodies so that they can remedy unhealthy living patterns. In order to achieve this goal, an understanding of what the biofeedback apparatus is measuring and what is the significance of these measurements is crucial. Such knowledge is vital for the active participation of subjects in the biofeedback process.

The first stage of system operation is the User Education (UE). During this stage, the user acquires the necessary knowledge to adeptly use the OSC application. The learning material covers the following topics:

- Introduction to ANS and an exploration of its two branches (PNS and SNS)
- Explanation of the significance of HRV and its relation to the ANS
- Description of the HRV parameters the OSC measures:
 - HF is associated with PNS (therefore an increase in HF suggests an activation of the PNS and a decrease implies the opposite)

- LF/HF is associated with the balance between SNS and PNS (therefore an increase in LF/HF implies a dominance of SNS over PNS, while a decrease indicates the opposite)
- Heart Rate (HR) indicates the number of heart beats in a minute and can be increased by various factors, one of which is mental stress (especially during periods of low activity)
- SDNN is associated with the general health of the ANS as it reflects all the sympathetic and parasympathetic components

5.1.1.2 System Training Stage

The second stage of operation is the System Training (ST). The system takes measurements of the user's physiological data over a certain period of time. This process is expected to run for at least one hour (not necessarily continuously) during which the user is performing low to moderate stress inducing tasks such as mundane work assignments. The latter period was chosen heuristically in order to grant the system enough time to observe the natural variations that occur in the HRV parameters during relatively low to moderate stress situations. The objective is to establish enough benchmark data regarding the expected parameters for a particular subject during low to moderate stress situations. Obviously, the longer the benchmark collection period is, the more accurate the stress detection will be in the next stage. This phase does not have to be performed in one contiguous session, but can be accumulated over an unlimited amount of sessions in order to gather enough training data.

5.1.1.3 Stress Monitoring Stage

The third and final stage of operation is the Stress Monitoring (SM). This is the biofeedback phase where the user can observe her or his physiological data as it is collected and analysed by the system. These collected measurements are continuously contrasted against the benchmarks. Also, in the event where an acute stress situation is detected, the user

is automatically given the option to engage in a guided relaxation process in order to interrupt the potentially perilous stress episode.

5.1.2 Office Stress Check Application Design

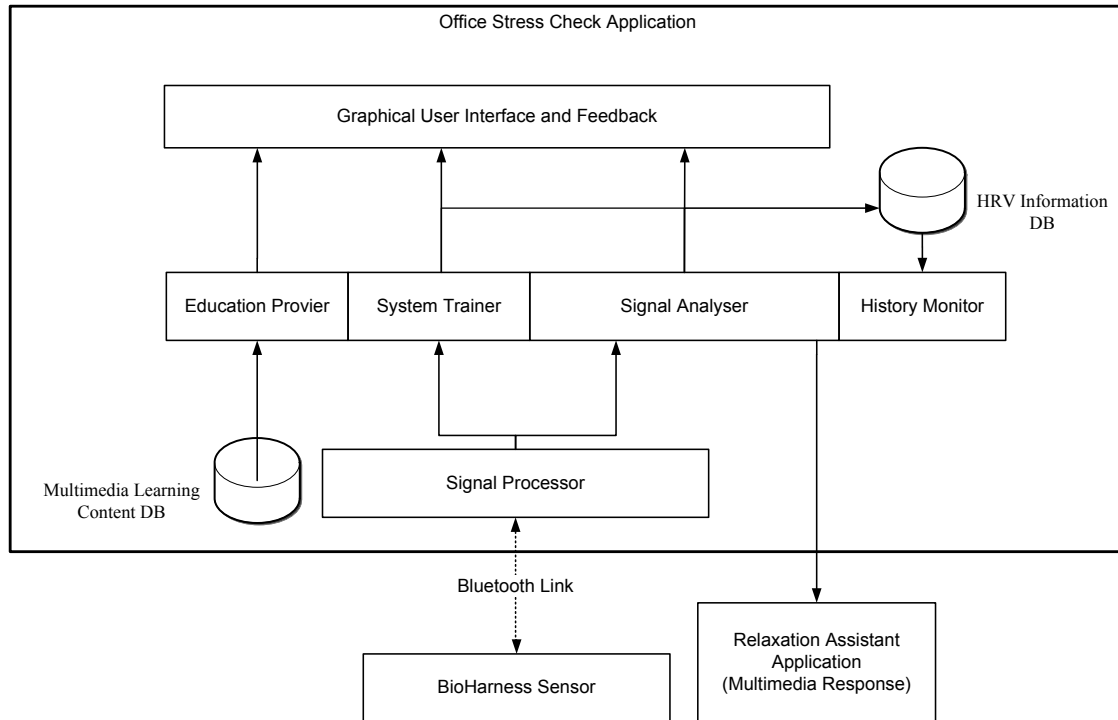


Fig. 5.3 Office Stress Check Application Architecture

The architecture of the OSC is shown in Figure 5.3. The application follows the U-Biofeedback reference model (presented in Chapter 3) by implementing its various components: Signal Processor, Signal Analyser, Feedback, History and Multimedia Response modules. In the subsequent Sections, we will present the details of the system's modules (shown in Figure 5.3). Note that the details of the Sensor and Signal Processor modules have been presented in Chapter 4 (they are generic modules and can be used by any stress management U-Biofeedback system) and therefore will not be discussed in this Chapter.

5.1.2.1 Education Provider Module

This module runs the “User Education” stage to teach users about the ANS, HRV and their relationship, through a set of learning material composed of text, images and video. The material is retrieved from the Multimedia Learning Content Database and relayed to the user via the GUI where the information is displayed using a sequence of dialog boxes that lead the user through a series of learning steps (see Figure 5.4). The user can move back and forth between the dialog boxes to review information previously learned. It is assumed that the user does not have any prior knowledge of the topic and therefore information is presented in an easy to grasp manner.

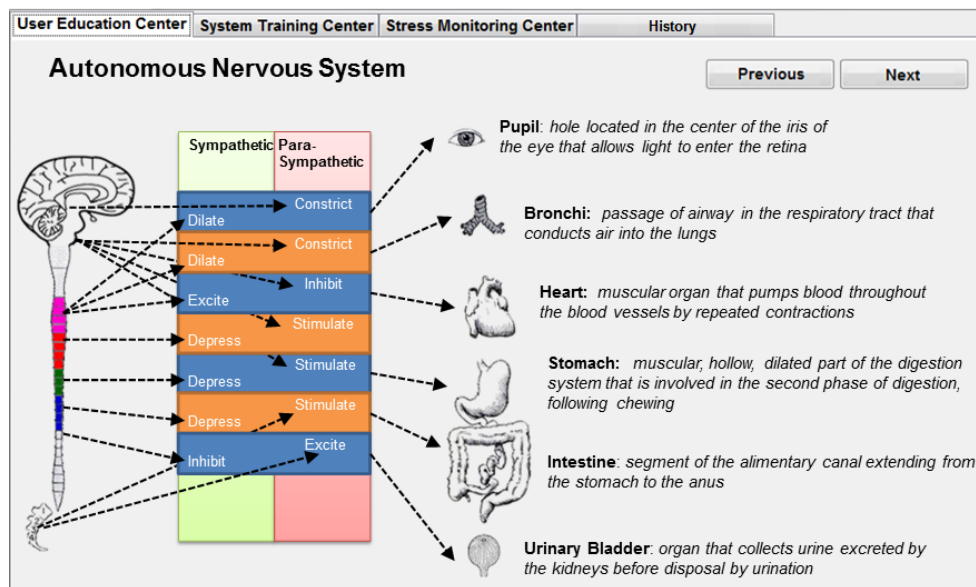


Fig. 5.4 OSC Education Provider Interface

5.1.2.2 System Trainer Module

This module runs the “System Training” stage. It is responsible for collecting the HRV information coming from the Signal Processor, relaying it to the HRV database for long term storage and the GUI for real-time display. The HRV information stored in the database is composed of a timestamp, the four HRV parameters being tracked, namely HF, LF/HF, HR and SDNN and the IVMU. Note that the LF parameter has been dropped since it is not known to reflect mental stress levels on its own.

Figure 5.5 shows the GUI controlled by the System Trainer module. A Color Coded Bar (CCB) is allocated for each parameter (HF, LF/HF, HR and SDNN). The green color at the center of the CCB symbolizes the mean value of all stored instances of that particular parameter. Colors on the CCB change gradually from green to red to symbolise the distance of an HRV measurement from the mean. A numerical scale is then superimposed over the bottom of the CCB, with the mean being at the center. The resolution of the numerical scale is calculated in a way to accommodate all previously collected data points (which are displayed as gray dots on the CCB). Every time a new measurement is collected, the CCB is redrawn so that the mean value falls exactly at its center. Also, the latest collected data point is displayed graphically as a blue indicator on the CCB.

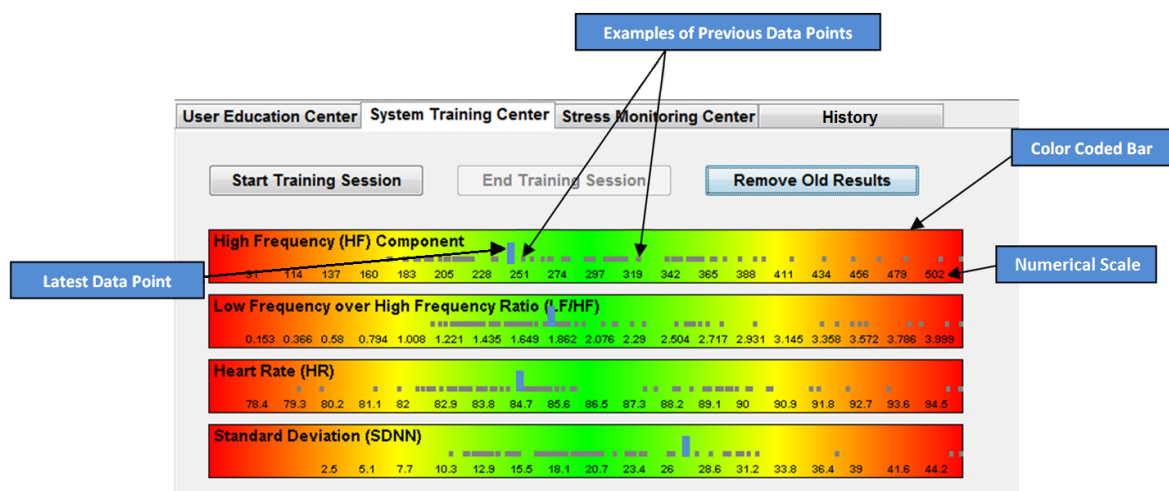


Fig. 5.5 OSC System Trainer Interface

5.1.2.3 Signal Analyser Module

This module runs the “Stress Monitoring” stage. It collects the HRV information from the Signal Processor and relays it to the GUI. It also examines the signal over time to detect potential acute stress events. These events are detected using the acute stress detection algorithm presented in Chapter 4. Whenever such events are identified, the Relaxation Assistant application is automatically started (subject to the approval of the user). Figure 5.7

shows a UML activity diagram describing the dynamic behavior of the Signal Processor and Signal Analyser modules.

The GUI controlled by this module displays the data collected during the training phase as a series of gray dots on the CCB. In Figure 5.6, the Normal Values Range (NVR) is shown as the non-darkened part of the Color Coded Bar. Users can modify the default NVRs at any time by dragging the edge of the non-darkened area to the appropriate place on the CCB using the computer mouse (if they judge them to be too flexible or too strict).

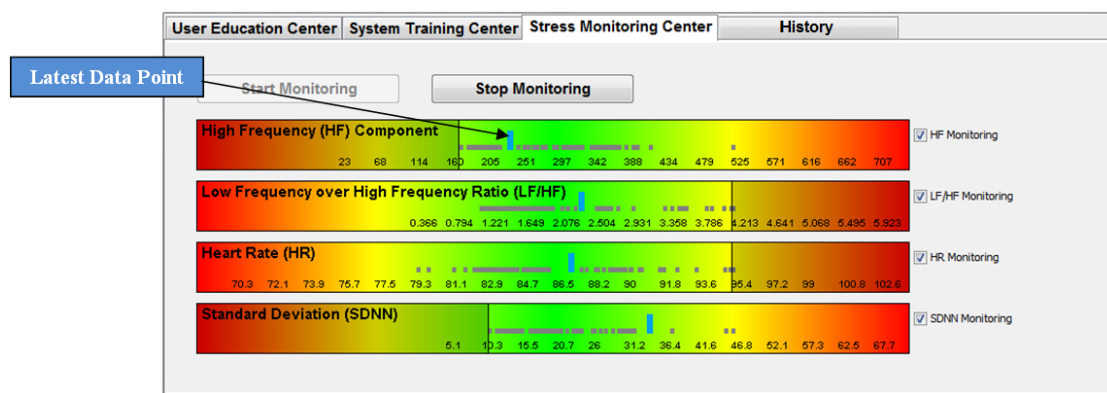


Fig. 5.6 OSC Signal Analyser Interface

5.1.2.4 Graphical User Interface and Feedback Module

The Graphical User Interface (GUI) and Feedback module is responsible for the following:

- Presenting the learning material during the “User Education” stage
- Presenting the measured parameters during the “System Training” stage
- Presenting the relevant feedback during the “Stress Monitoring” stage (and thus allowing users to glance from time to time at the values of the measured HRV parameters).

Also, whenever an acute stress event is detected by the Signal Analyser module, a system tray popup prompts the user whether she or he would like to launch the Relaxation Assistant Application. If ignored, the popup disappears in 3 minutes.

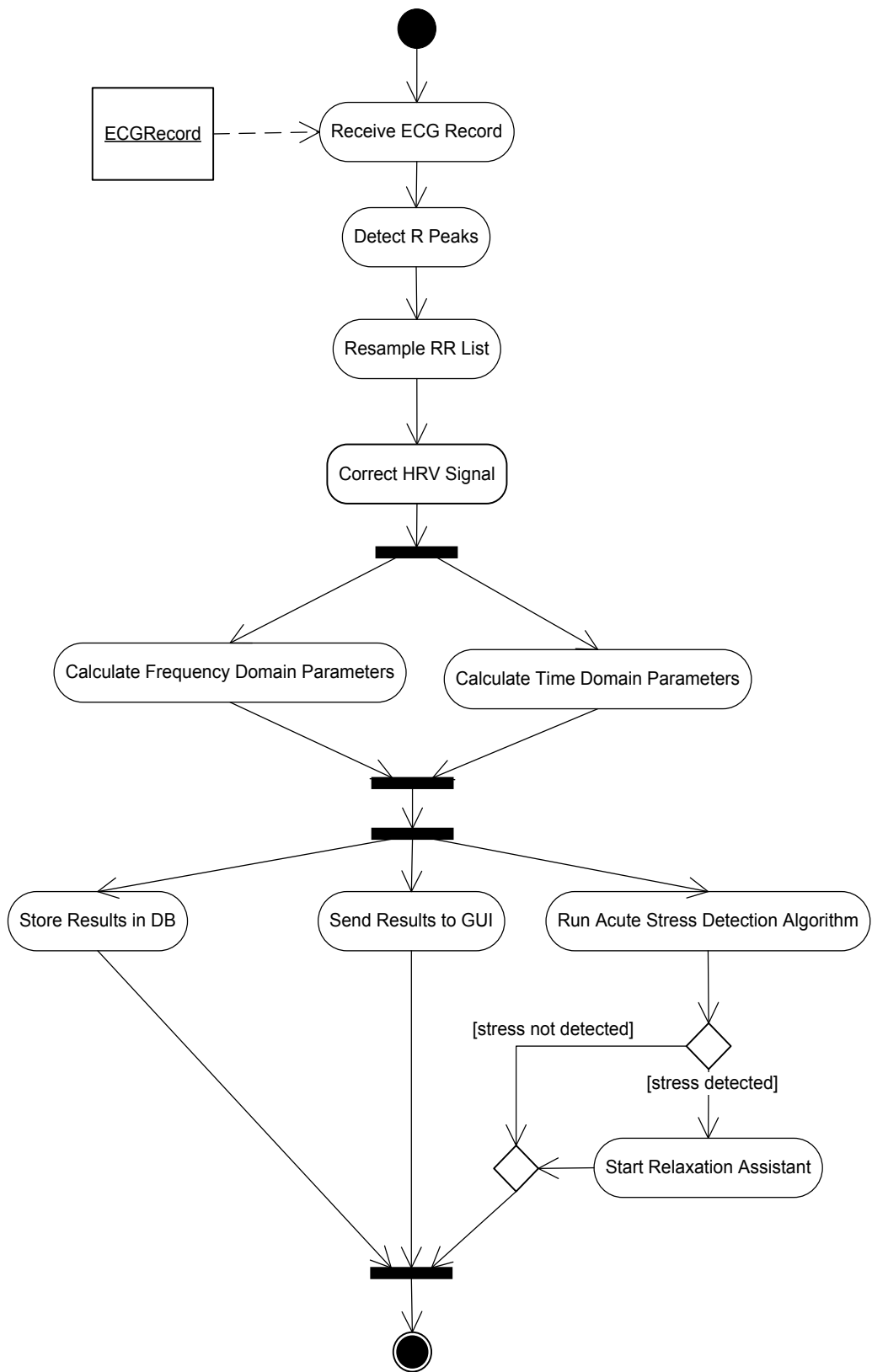


Fig. 5.7 Behavior of the Signal Processor and Signal Analyser Modules

5.1.2.5 History Motoring Module

In addition to the aforementioned functionality that compose the awareness process, the OSC allows, as part of the assistive process, users to review previously measured HRV parameters through the use of automatically generated Comma Separated Values (CSV) files. The files are generated for a user-defined time period and granularity. The CSV format is readable by many spreadsheet software tools and thus simplifies the process of generating graphs from of the contained information. Nonetheless, in future iterations of OSC, we plan on integrating the graph generation functionality within the application itself so as to reduce the steps involved in reviewing history of measurements.

5.1.3 Relaxation Assistant Design

The Relaxation Assistant Application implements the Multimedia Response defined in the U-Biofeedback reference model. It randomly loads one of five available videos that guide users to perform a deep breathing exercise. The length of the videos ranges from 10 to 16 minutes. Deep breathing exercises are widely recommended by meditation experts and have been known to help reduce anxiety and stress [72].

5.1.4 Office Stress Check and Relaxation Assistant Implementation

The OSC and Relaxation Assistant applications were both implemented in Java SE 7 with the GUI customized for the Windows 8 platform. The communications between the BioHarness sensor and the OSC is performed over a Bluetooth link. The specification for the communication messages supported by BioHarness is described in [89].

5.2 Evaluation of Office Stress Check

5.2.1 Lab Experiment

We have conducted an in-lab experiment on subjects to monitor the changes in their HRV parameters during stressful situations. The experiment is needed to assess the validity of our setup which is composed of a program performing real time measurements on information received from the BioHarness sensor. More importantly, while many papers cover the topic of mental stress and its effects on HRV, various factors can affect the values obtained for the frequency domain parameters (sampling rate and PSD method). Therefore, it is important to establish a baseline for our configuration that will be used for long term monitoring.

Six consenting adults, 2 females and 4 males, between the ages of 22 and 33 (26.7 ± 4.59) years old took part in the experiment. None of the subjects had a known history of heart or mental health disease. None of the subjects were taking anti-anxiety or anti-depression medication. The experiment took place in a laboratory setting, where participants were isolated from external influences that might have affected the outcome. Throughout the experiment, subjects were seated in a typical, ergonomically sound, office chair in front of a computer.

The experiment was divided into three phases of 9 minutes separated by 6 minutes of rest (see Figure 5.8). A description of these phases is provided in the next three sections.

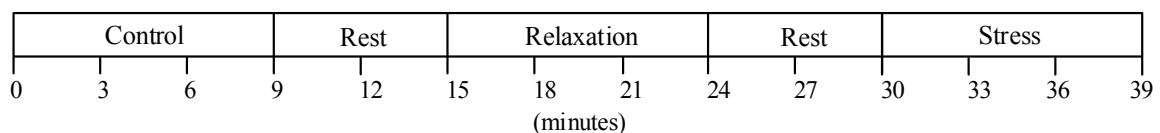


Fig. 5.8 Various Phases of the First Experiment

5.2.1.1 Control Phase

The first phase was considered the control one where the user was asked to perform a low to moderate stress inducing task. In order to do so, users were asked to relax their muscles

and clear their thoughts as much as possible. The task consisted of a 9 minutes typing exercise driven by a simple computer program that displays 6 randomly generated digits. The user has to type these digits within a time period of 4 seconds ($\frac{2}{3}$ of a second per digit) before another set of digits is displayed. The exercise is designed to simulate “slightly” stressful work with minimal cognitive requirements. Finsen et al used a similar experiment to simulate computer work [90]. Before the start of this phase, all subjects were asked to assess their levels of stress using the Visual Analogue Scale (VAS) of perceived stress. VAS is a psychometric response scale which is used to subjectively assess the experiences of subjects by specifying their level of agreement with a statement on a scale between two endpoints. The scale was printed on a paper as a 100 mm unmarked ruler as shown in Figure 5.9 and was accompanied with the following instruction: “Indicate how stressed you feel on the small ruler”. Given the mark left by the subjects on the scale, a crisp value between 0 and 100 reflecting their subjective sensation of stress can be retrieved. The effectiveness of VAS as a quick self-reported stress assessment tool has been demonstrated in [87]. All subjects reported a level of stress below the 20 threshold before the start of this phase and a level below the 50 threshold after its completion on the VAS scale. This ensured these measurements can also be used as benchmarks (according to the definition presented in Section 4.3.1).

5.2.1.2 Relaxation Phase

In the second phase, the user engages in a guided imagery and breathing exercise by following instructions from a video. Such exercises have been widely used to relieve stress and were recommended as relaxation techniques in [72].

5.2.1.3 Stress Phase

For the third phase, the user was given a timed mental arithmetic task driven by a computer program. The task consisted of answering consecutive multiplication questions involving

numbers between 0 and 12 within a time limit. The initial Time Per Question (TPQ) is 2 seconds. Nonetheless, the latter value is adapted depending on the performance of the user. The adaptation mechanism simply increases the TPQ by 0.1 seconds per mistake up to a maximum of 4. It also decreases the TPQ by 0.1 seconds after 2 consecutive correct answers down to a minimum of 2 seconds. This is designed to ensure that less skilled users remain engaged by the task. We wanted to avoid situations where subjects would find the exercise too difficult (or too easy after a start marred by few mistakes) and subsequently lose interest. After every 10 consecutive questions, the game is paused for 2 seconds and the score is shown on the screen in an oversized font. The score is formatted as the number of correct answers out of the total amount of questions. This is intended to continuously draw the attention of the user towards her or his progress. Also, the subjects were lead to believe that in addition to stress monitoring, through the arithmetic exercises, their cognitive abilities were being tested and compared to those of their peers. This is designed to accentuate a subject's feeling of stress.

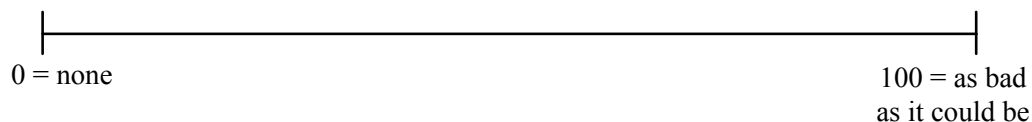


Fig. 5.9 Visual Analogue Scale of Perceived Stress

5.2.1.4 Discussion of Results

Table 5.1 shows \overline{HF} and $\overline{(LF/HF)}$ values for each subject during the three phases of measurement. Note that the former is the average HF value and the latter is the average (LF/HF) for an entire phase. On average, for all subjects, \overline{HF} increases during relaxation and decreases during stress compared to the benchmark. Also, $\overline{(LF/HF)}$ decreases during relaxation and increases during stress compared to the benchmark. This is expected as an

increase in HF or a decrease in LF/HF signals relaxations and consequently a decrease in HF or an increase in LF/HF signals stress [42, 43, 44, 45 and 46].

Table 5.1 –Average of Relevant HRV Parameters during the Phases of the Experiment

Subject Number	Control Session				Relaxation Session				Stress Session			
	\overline{HF}^1	$\overline{(LF/HF)}$	\overline{HR}^2	\overline{SDNN}^3	\overline{HF}^1	$\overline{(LF/HF)}$	\overline{HR}^2	\overline{SDNN}^3	\overline{HF}^1	$\overline{(LF/HF)}$	\overline{HR}^2	\overline{SDNN}^3
1	291	2.33	72	30	3875	2.96	72	61	348	7.64	76	33
2	902	1.65	83	41	2531	1.49	82	50	900	2.28	83	40
3	903	1.67	78	35	1601	1.83	78	40	803	2.44	85	38
4	155	2	89	21	258	1.47	87	41	105	2.97	93	15
5	2540	0.869	64	92	2869	0.726	62	112	1430	1.72	72	74
6	643	1.89	74	41	3876	2.96	74	52	585	2.14	78	40
Average	906	1.73	77	43	2502	1.91	76	59	695	3.20	81	40
STDEV	858	0.49	9	25	1397	0.89	9	27	464	2.21	7	19
¹ : Expressed in ms^2				² : Expressed in ms				³ : Expressed in heart beats per minute				

5.2.2 *Long term Experiment*

We have evaluated the effectiveness of our stress management system for a period between 13 and 17 days on 3 consenting adult subjects. The subjects were asked to refrain from the following activities for the duration of the experiment: drinking coffee or any other stimulants, consuming alcohol and smoking. A chart of relevant subjects' information is presented in Table 5.2. All of the subjects spend most of their working days sitting in an office chair in front of a desk with a computer screen mounted on top. They perform various tasks on the computer such as viewing and sending emails, reading and writing documents and programming. The OSC application was executed on an adjacent Windows Surface tablet and the subjects were encouraged to glance at their HRV parameters from time to time. The User Learning stage was completed at home outside of work hours. The System Training stage was completed during the weekend where the subjects took prior permission from their managers to work on mundane, low or moderate stress inducing tasks. Working on the weekend allowed them to choose the tasks they were interested in performing without any pressure from their superiors or peers. As for the System Monitoring stage, the measurements were taken during regular work hours. Table 5.3 shows a summary of the subjects' daily use of the OSC. For the length of the monitoring stage, users were asked to periodically (every 30 to 60 minutes) and subjectively indicate their stress levels using the Visual Analog Scale (VAS) presented in Figure 5.9. They were also asked to note episodes where they feel the amount of stress they experience is negatively affecting their work performance by writing down the time and the task they were performing in a log. We used this information to assess whether the OSC missed an acute stress event that was experienced by the subject. Note that we assumed that an acute stress event corresponds to a value of 70 or greater on the VAS. Also, whenever the OSC displays a stress warning, the subjects were asked to note if they

agree with the assessment. Table 5.4 shows a summary of the results based on the subjective user assessment. These results show that the algorithm, on average for the three subjects, correctly identified acute stress episodes 89.63% of the times with an average false detection rate of 5.55%. At the end of the experiment, the users filled a questionnaire to rate their experience (see Table 5.5). Their responses show that they were satisfied with the performance of the OSC and its relaxation assistant. Also, two of the subjects reported very little discomfort wearing the BioHarness device for a prolonged period of time, while one subject reported moderate discomfort.

Table 5.2 Subjects Description

Subject Number	Gender	Age (Years)	Weight (Kg)	Duration of Use (Days)	Occupation Description
1	Female	29	64	16	Quotes Coordinator: responsible for presenting quotes for new science start-ups to potential customers.
2	Male	28	85	17	Graduate Student: responsible for running lab experiments and evaluating results.
3	Male	26	82	13	Software Designer: responsible for writing software modules for a commercial product.

Table 5.3 Summary of the Daily Use of the OSC by the Subjects

Subject Number	OSC Daily Use (Hours)																
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	3.0	5.3	4.2	4.1	3.2	5.6	6.1	5.4	5.4	4.2	3.6	3.5	6.2	4.7	5.8	6.0	0.0
3	1.6	4.0	5.0	5.3	1.7	2.9	5.1	7.0	7.2	5.3	4.6	4.6	6.2	4.9	5.4	5.6	1.4
3	2.4	4.0	4.6	3.9	4.3	5.7	4.2	3.9	6.2	6.5	4.3	5.9	0.0	0.0	0.0	0.0	0.0
Days	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Legend:																	
User Learning Phase						System Training Phase						Stress Monitoring Phase					

Table 5.4 OSC Stress Detection Results (according to the user subjective assessment)

	Subject 1	Subject 2	Subject 3	Average
Total Distinct Acute Stress Events (identified by user, OSC or both)	9	5	6	6.67
Acute Stress Events Identified by the User	9	5	5	6.33
Acute Stress Events Detected by OSC	8	4	6	6.00
Acute Stress Correctly Identified by OSC (according to the user)	8	4	5	5.67
Instances Incorrectly Identified as Acute Stress Events by OSC (according to the user)	0	0	1	0.33
Acute Stress Events Missed (Not Caught) by OSC (according to the user)	1	1	0	0.67
False Positive Acute Stress Detection Rate	0%	0%	16.67%	5.55%
True Positive Acute Stress Detection Rate	88.89%	80.00%	100%	89.63%

Table 5.5 Questionnaire Filled by the Subjects at the end of the Experiment

	Subject 1	Subject 2	Subject 3
On a scale of 1 to 10 how effective is the OSC as a stress management tool (10 being the most effective)?	8	8	9
On a scale of 1 to 10 how efficient was the relaxation manager in diffusing stressful situations (10 being the most efficient)?	6	7	9
On a scale of 1 to 10 how uncomfortable was it to wear the BioHarness device for long periods of time (10 being the most uncomfortable)?	1	3	5

5.3 Biofeedback Serious Game Case Study

A serious game is an application that intertwines two complementing scenarios: a utilitarian scenario and a gaming scenario [79]. Both scenarios must coherently converge into a resultant engaging application that provides an entertaining and utilitarian value. In this Thesis, we formalize the concept of Biofeedback Serious Games (BSGs). This notion is a specialization of the aforementioned definition of the serious games in that the utilitarian scenario is a biofeedback one. Figure 5.10 portrays the spectrum of applications ranging from

games purely aimed at entertainment to biofeedback systems lacking a gaming scenario. BSGs fall at the intersection of these types of applications. Therefore, we can define a BSG as a game that takes as input one or more biological signals, analyses them, and produces relevant feedback within the game’s scope. In fact, the game serves as a medium to intuitively (and possibly metaphorically) present the results of the signals’ analysis. Such result should directly affect the game’s progress or outcome. Also, there should be a clear and intuitive mapping between the monitored physiological process and the presented results depicted by the game. Such presentation completes the essential feedback loop required in a biofeedback system.

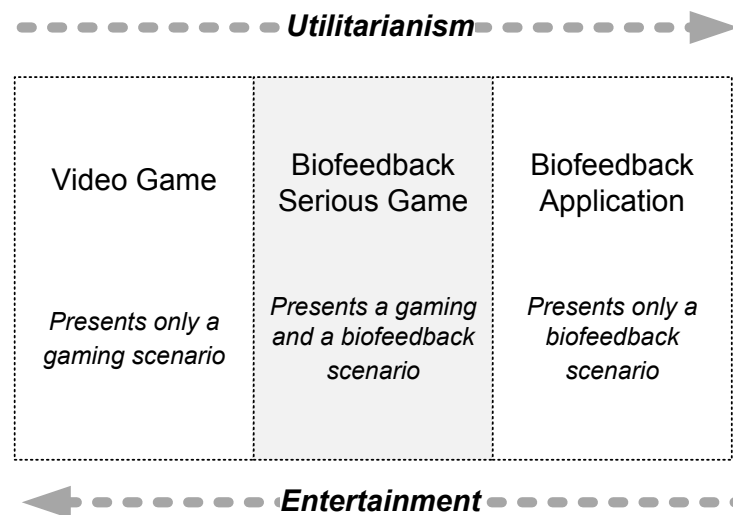


Fig. 5.10 BSGs as the Intersection between Video Games and Biofeedback Applications

5.3.1 Biofeedback Serious Game Description

We describe in this section, a Biofeedback Serious Game that implements the U-Biofeedback framework. We call the game “Botanical Nerves” and it runs exclusively on mobile platforms (Android in particular). The central, and only, character of the game is a tree. It represents the status of the Autonomous Nervous System (ANS) of the player. Therefore, whenever the player is experiencing stress, the health of the tree deteriorates. This

is conveyed through an animation of the tree leaves yellowing and eventually falling. However, when the player relaxes, more leaves grow, the existing ones become greener and the tree starts to flower (see Figure 5.11). Also, textually, the same information is conveyed through a tree health indicator. In order to inject a dimension of competitiveness, a score is displayed on the main game screen. The score reflects the improvements of the health of the tree over time. Although many games have eliminated the notion of score, we find it useful in our particular scenario as it summarizes well the overall performance over a period of time. Also, it allows for the comparisons between various gaming sessions to look for particular positive or negative trends formed over time.

The game runs in two modes: limited time and indefinite. In the limited time mode, the player sets the time period of monitoring. In the indefinite mode, the monitoring goes on indefinitely as long as the game is running. Note that the game interface can be relegated to the background while other operations are performed on the phone.

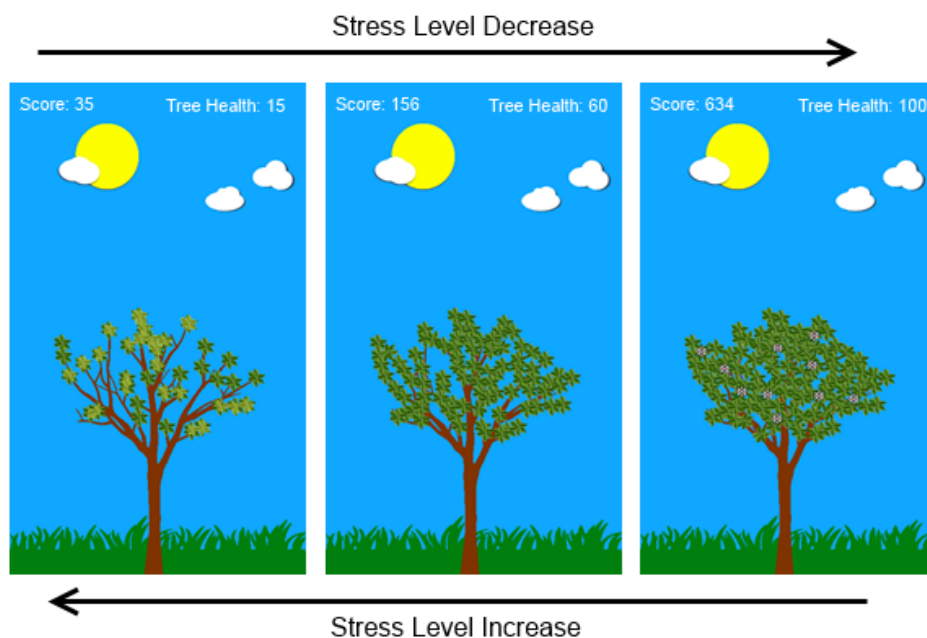


Fig. 5.11 Screen Shorts of the BSG as Stress Increases or Decreases

5.3.2 *Biofeedback Serious Game Design*

As we have previously mentioned, the present system strictly follows the U-Biofeedback reference model detailed in Chapter 3. The following Sections describe the implementation of the various modules defined in the aforesaid model in the context of a Biofeedback Serious Game. All modules characterized below are software components that belong to the gaming application running on the Android device. The Sensor and Signal Processor modules have already been described in Chapter 4. Nonetheless, the following modules have been implemented specifically to meet the requirements of this application and therefore will be described in details in the next Sections:

- Signal Analyser Module
- Feedback Module
- History Monitoring Module
- Relaxation Assistant (implement the Multimedia Response)

5.3.2.1 *Signal Analyser Module*

The Signal Analyser module processes the collected HRV information to detect acute stress events. Also, it keeps track of the accumulation of stress the user is experiencing. Both of these methods were introduced in Chapter 4. The stress accumulation in particular is used to calculate the corresponding health of the tree. The details of this relation are explained in the next Section.

5.3.2.2 *Feedback Module*

Feedback is necessary to complete the control loop between the body and the mind. Therefore, the system provides two forms of feedback: graphical and numerical.

In order to provide meaningful feedback to the player, the stress accumulation must be mapped to an important component of the game. In our case, it is the health of the tree, which

metaphorically represents the wellbeing of the player. When mapping the stress accumulation to the health of the tree, we need to balance two requirements:

- The player should be able to promptly observe the effects of her or his relaxation on the health of the tree. This will increase the level of engagement in the game and provide for a meaningful biofeedback experience.
- The health of the tree shall not only depend on the instantaneous physiological information of the user, but also have an element of history to reflect stress accumulation. This is especially necessary to encourage players to remain relaxed for long periods of time in order to succeed in the game. We want to avoid situations where users engage in short bouts of relaxation that unrealistically boost their sense of accomplishment while not reflecting an overall trend of stress management and emotional control throughout the period of play.

In order to balance these two requirements, when calculating the stress accumulation for immediate feedback purposes, we opted to use the kernel function presented in Equation (4.8). This function places more emphasis on the latest measurements and therefore allows the player to observe relatively quickly the effects of relaxation on the game. The size of the kernel should be relative to the game play period. For prolonged monitoring, we set the kernel size at 120 and therefore, the stress accumulation value calculated in Equation (4.5) reflects the last hour worth of measurements (given that a measurement is made every 30 seconds).

The numeric feedback represents the score that the player has achieved. This is calculated using Equation (5.3) and represents the accumulation of tree health improvements throughout the period of play. The graphical feedback is tied to the health of the tree that represents the status of the ANS. The health is calculated using Equation (5.1) and then capped between

zero and β using Equation (5.2) where an $hc[n]$ value of zero represents the worst tree health possible (all the leafs have fallen) and $hc[n]$ value of β represents the best possible tree health. Initially, at the beginning of the game, the health of the tree is set to $\beta/2$. In Equation (5.1), the value of δ amplifies deviations of the measured HRV parameters from their respective benchmarks. This value can be set by the operator. In our experiments, we have set δ to 13 as we felt it resulted in a good sensitivity level with regards to HRV fluctuations. The value of β (in Equations (5.1), (5.2) and (5.3)) was set to 100.

$$h[n] = \frac{\beta}{2} + \delta \times SA[n] \quad (5.1)$$

$$hc[n] = \begin{cases} \beta, & \text{if } h[n] > \beta \\ h[n], & \text{if } 0 \leq h[n] \leq \beta \\ 0, & \text{if } h[n] < 0 \end{cases} \quad (5.2)$$

$$s[n] = s[n - 1] + \max(h[n] - \frac{\beta}{2}, 0) \quad (5.3)$$

The tree health feedback reflects the stress accumulation over a period of time. We also would like to a monitor acute stress manifestation. Rather than looking at accumulative effects, we want to identify abrupt jumps in stress levels. It would be ideal if we can interrupt such episodes whenever they are detected. We used the algorithm presented in Section 4.3.2 to identify such phenomenon.

5.3.2.3 History Monitoring Module

Long term trends are important for biofeedback exercises, where a player can identify potentially positive or negative trends in the data accumulated over time and across many sessions of monitoring. In fact, for a player, all physiological information (HF, LF/HF and IVMU) gathered during game play are stored in the database for later review. Most importantly, the user can analyse the stress accumulation over time. Nonetheless, since the focus is on long term trends here, in the calculation of the stress accumulation (using Equation (4.5)), the kernel function presented in Equation (4.7) is used with a size that can be

adjusted by the operator (default size of 2280 to reflect 24 hours' worth of measurements). Using this kernel function in the calculation of stress accumulation, the weight for each stress index is gradually and linearly decreased depending on how old is the measurement.

5.3.3 Relaxation Assistant Design

Just the like the OSC, a Relaxation Assistant application implementing the Multimedia Response of the U-Biofeedback model is associated with the Botanical Nerves game. Whenever an acute stress event is detected (using the algorithm of Section 4.3.2), the user is immediately warned of the situation (through the standard Android notification mechanism) and given the option of starting a relaxation process. If the user accepts to engage in the process, a guided meditation or breathing exercise instructional video will run on the mobile phone to assist the player in achieving a state of relaxation. Note that these notifications can be disabled by the user if she or he deems them to be unnecessary.

5.3.4 Biofeedback Serious Game and Relaxation Assistant Implementation

The game and relaxation assistant were implemented in Java and executed on an Android 4.3 platform. The standard Android API was used to render the 2D animation onto an Android Canvas for the game. The biological sensor used to collect physiological information is Bioharness from Zephyr [71]. A Bluetooth connection is established between the sensor and the mobile phone to enable wireless communication. We used the Android Java library developed by Zephyr to interact with the sensor.

5.4 Evaluation of the Biofeedback Serious Game

5.4.1 Lab Experiment

Using Equations (5.2) and (5.3), we calculated the tree health and score on the HRV data obtained from the experiment detailed in Section 5.2.1. This information is captured in Table 5.6 which presents the following:

- \overline{hc} : average tree health during a session
- $\min(hc[n])$: minimum tree health reached during a session
- $\max(hc[n])$: maximum tree health reached during a session
- $\max(s[n])$: maximum score reached during a session

Note that the Control session results were considered to correspond to the benchmark when we performed the calculations. This is valid since the Control Session represents an exercise that induces low to moderate level of stress (which was also verified using the VAS subjective test). Also, the tree health and score was reset at the beginning of each phase.

We notice from Table 5.6 that the average and maximum tree health, expressed as \overline{hc} and $\max(hc[n])$ respectively, increase during relaxation and decreases during stress consistently for all subjects. Likewise, the score reached during a session, expressed as $\max(s[n])$ is significantly higher during the relaxation compared to stress.

Therefore, by completing this exercise, we have verified that tree health and score parameters reflect well the stress or relaxation status of individuals.

Table 5.6 Game Related Parameters during Relaxation and Stress

Subject Number	Relaxation Session				Stress Session			
	\bar{hc}	min(hc[n])	max(hc[n])	max(s[n])	\bar{hc}	min(hc[n])	max(hc[n])	max(s[n])
1	82.20	48.43	100	945	45.20	37.28	53.08	6
2	78.58	60.12	90.77	532	45.93	35.97	54.57	21
3	63.66	51.83	69.50	257	48.29	37.63	55.09	26
4	66.31	51.33	81.55	308	41.46	36.58	48.96	0
5	59.23	49.12	65.12	236	33.45	26.49	47.65	0
6	83.45	63.47	100	764	43.49	36.48	52.19	17

5.4.2 Extended Experiment

In addition to the controlled short term experiment presented above, an extended experiment was conducted on the same subjects. The experiment's goal was to allow players to use the BSG during regular work days in order to observe its ability to help them control their stress levels. The metrics that will be monitored during the experiment are the tree health and the score, which we have previously established to be a good reflection of the relaxation or stress status of a subject. Table 5.7 lists the various phases involved in the experiment along with the duration and description of each.

Table 5.7 Phases of the Long Term Experiment

Phase	Duration (minutes)	Description
Benchmark Collection	60	During this phase, the benchmark was collected so that it can consequently be used to later assess the stress level of the subject. The perceived stress was measured using the VAS every 20 minutes and the session was considered valid only if the perceived stress remained throughout the collection period between 0 and 50

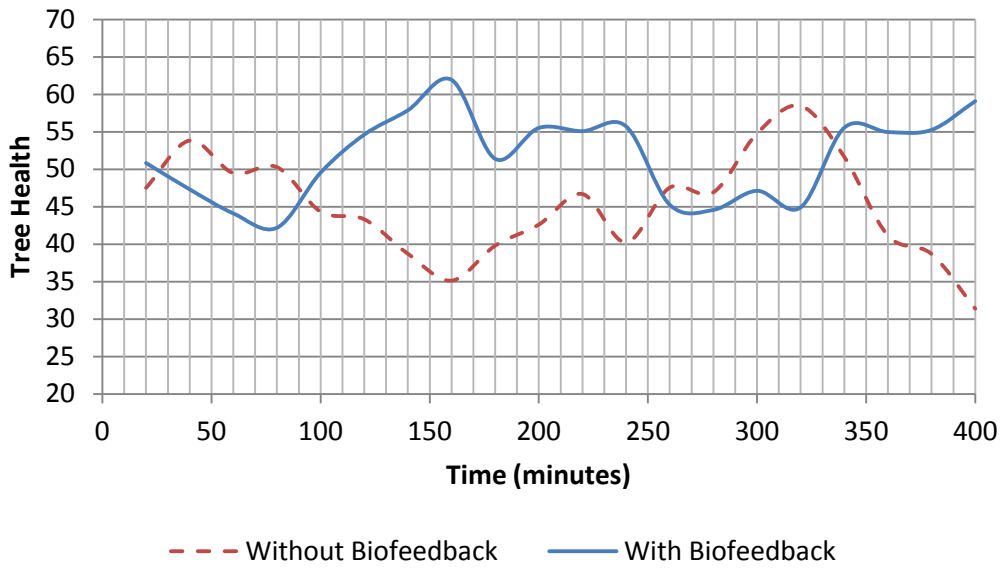
		on our scale.
Work without Biofeedback	400	During this phase, the subject was asked to use the system 80 minutes every day for a working week. Nonetheless, the user interface of the BSG was hidden and thus breaking the feedback loop necessary for biofeedback applications. However, we still collected the tree health and score without disclosing them to the subject.
Work with Biofeedback	400	During this phase, the subject was asked to use the system 80 minutes every day for a working week. This time, we introduced the subjects to the BSG and told them that the goal of the game is to maximize their score and thus keep the tree as healthy as possible. They were told that if they are interested in increasing their score, they can engage in guided meditation or breathing exercises (instructional videos were included on the mobile phone platform for these exercises and can be run directly from the game interface). We also explained that in case of the detection of an acute stress situation, a warning message will ask them if they would like to engage in a relaxation exercise. We informed them that engaging in such exercises not only help them improve their score, but also reduce their stress level to achieve a higher level of wellbeing.

Table 5.8 summarizes the game parameters collected during the experiment where \bar{hc} is the average health of the tree throughout the experiment and $\max(s[n])$ is the maximum score

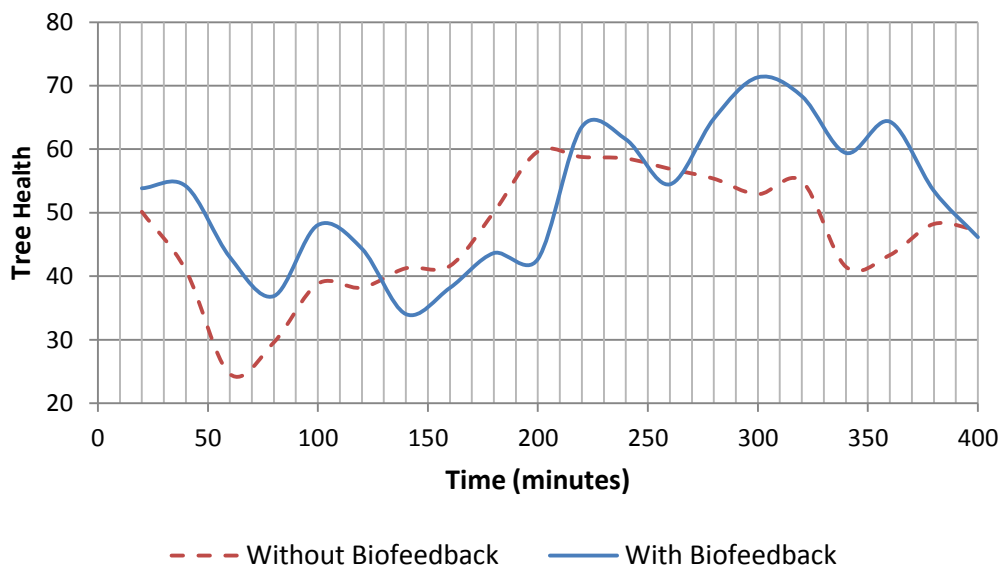
reached. In the case where the individuals were engaged in the game, and thus the biofeedback component was enabled, all the players (except for subject 5) were clearly able to achieve better score and tree health compared to the case where the game user interface was disabled. No significant difference between both phases (with and without biofeedback) was observed for subject 5. Consequently, we can postulate that five out of the six subjects (83.33% of the subjects) were better able to control their stress level whenever game based biofeedback was enabled. Figure 5.12 shows the evolution of the tree health for all subjects during both phases of monitoring.

Table 5.8 Game Related Parameters Collected during Long Term Experiment

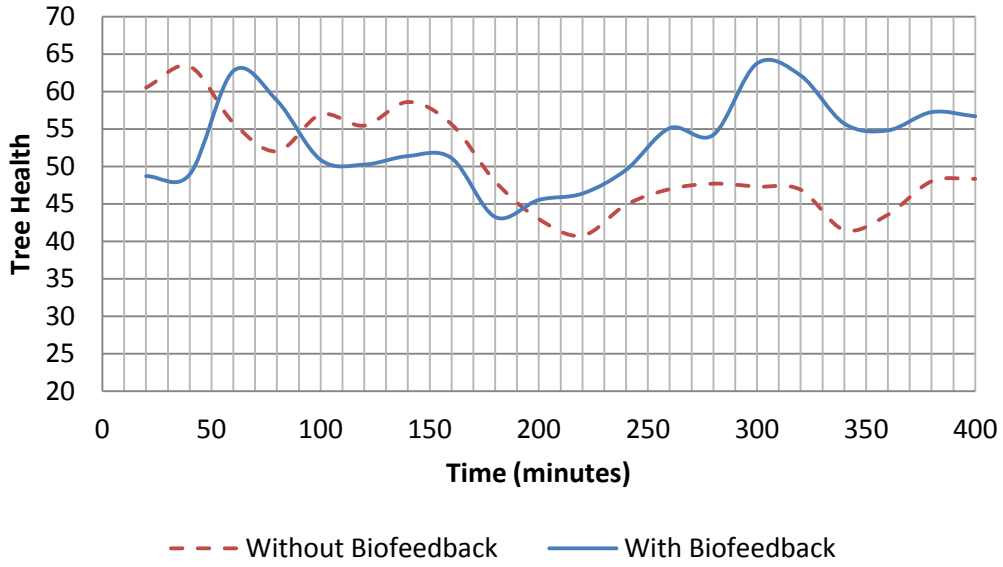
Subject Number	Without Biofeedback		With Biofeedback	
	\bar{hc}	max(s[n])	\bar{hc}	max(s[n])
1	45.12 (6.89)	918	51.64 (5.71)	3264
2	46.62 (9.75)	2270	52.31 (11.09)	5712
3	50.25 (6.59)	2797	53.35 (5.77)	4067
4	45.50 (4.39)	507	54.45 (7.88)	5738
5	50.23 (4.79)	2036	49.04 (6.60)	2229
6	46.53 (5.70)	937	52.42 (5.32)	3289
Average	47.38 (2.29)	1577.5 (913.03)	52.20 (1.83)	4049.83 (1423.01)



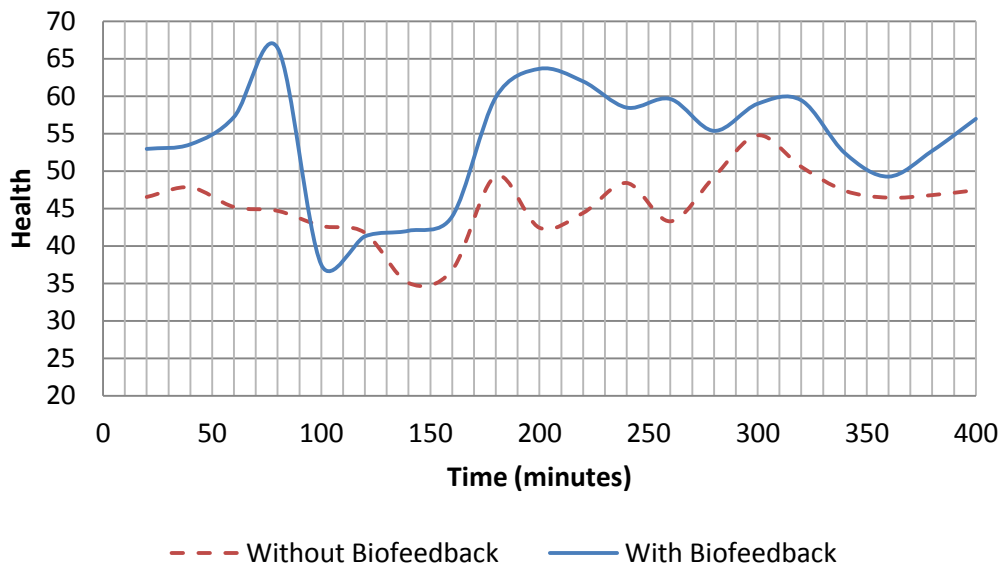
Subject 1 Performance with and without Biofeedback



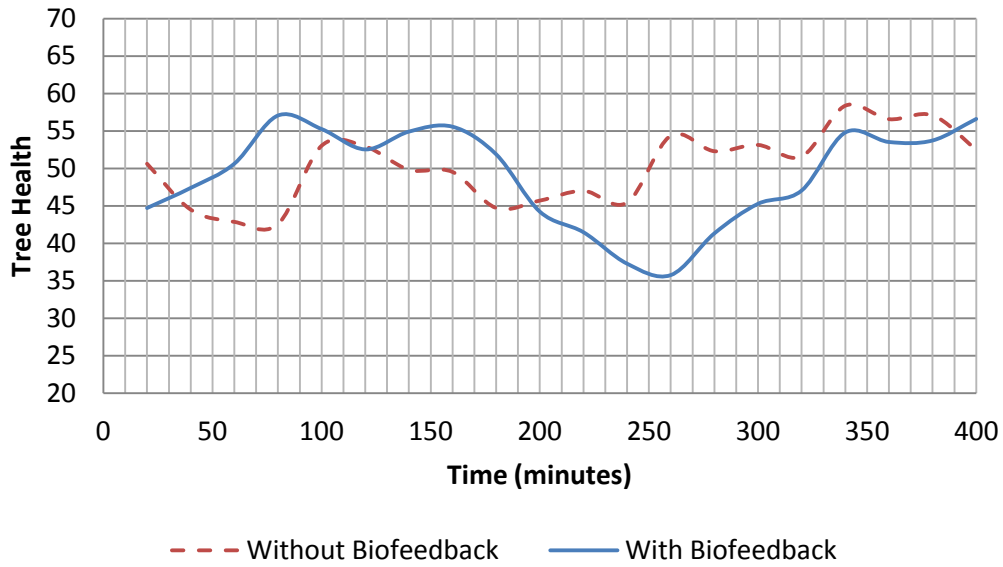
Subject 2 Performance with and without Biofeedback



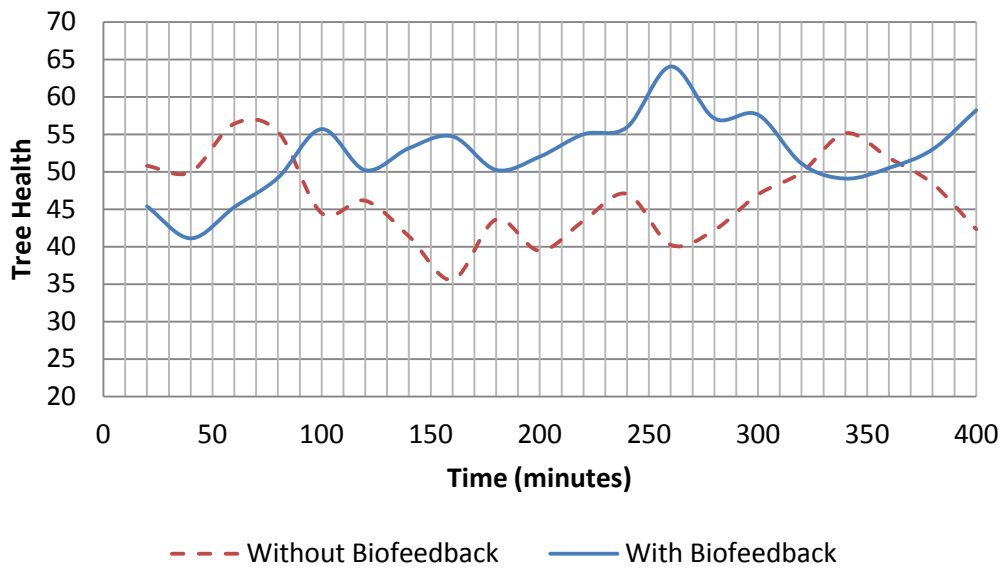
Subject 3 Performance with and without Biofeedback



Subject 4 Performance with and without Biofeedback



Subject 5 Performance with and without Biofeedback



Subject 6 Performance with and without Biofeedback

Fig. 5.12 Subjects' Performance with and without Biofeedback

5.5 Personalized Relaxation

The previous Sections present two U-Biofeedback stress management systems that make use of a simple Multimedia Response application that runs meditation or deep breathing

instructional videos. This application launches automatically when increased stress levels are detected.

In this Section, we present a Personalized Relaxation Assistant (PRA) that implements the personalized relaxation mathematical model described in Chapter 4. The model takes into account the user preference (what she or he perceives as relaxing) and the performance history of relaxation techniques (how well a relaxation technique worked during its previous applications). Nonetheless, before we introduce the PRA, we provide a simulation scenario of the aforementioned mathematical model that highlights its capability in terms of adapting the relaxation experience.

5.5.1 Simulation of the Personalized Relaxation Mathematical Model

5.5.1.1 Simulation Setup

By applying the mathematical model presented in Chapter 4, the personalization of the relaxation process works as follows:

- User completes a form to rank a list of relaxation techniques that she or he prefers or perceives as more effective. Examples of relaxation options include controlled breathing, listening to music, watching entertaining videos, physical exercises, etc... The idea is to distract the user's attention from the stressful situation so that it can be approached later with a more relaxed mind set.
- U-Biofeedback stress management system continuously monitors the stress level.
- When stressful situations arise, the system initiates the pre-customized stress response to reduce the stress emotion. Depending on the user's physiological reaction to the selected technique, the mathematical model will automatically update the prioritization of the available techniques.

In this simulation, we define the following relaxation techniques:

- | | | |
|--|-------------------------------------|------------------------|
| 1. Relaxing music | 6. Visualization | 10. Breathing exercise |
| 2. Relaxing images | meditation | 11. Massage |
| 3. Relaxing images
and music | 7. Deep breathing
meditation | 12. Funny videos |
| 4. Peaceful sounds | 8. Body scan | 13. Eating |
| 5. Relaxing images
and peaceful
sounds | 9. Progressive
muscle relaxation | 14. Napping |
| | | 15. Exercising |

Accordingly, α (described in Section 4.4) becomes a 15×15 matrix describing the correlation between any of the relaxation techniques. For instance the element at row 2 and column 3 describes the correlation between relaxation technique 2 (relaxing images) and technique 3 (relaxing images and music). Since they both share a common stimulus (i.e. images slideshow), they should be accorded a high correlation value. Therefore, an example representation for matrix α would look like the following:

$$\alpha = \begin{bmatrix} 1 & 0 & 0.75 & 0.5 & 0.5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0.75 & 0 & 0.75 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.75 & 0.75 & 1 & 0.5 & 0.75 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.5 & 0 & 0.5 & 1 & 0.75 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.5 & 0.75 & 0.75 & 0.75 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0.75 & 0.75 & 0.5 & 0.5 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.75 & 1 & 0.75 & 0.5 & 0.75 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.75 & 0.75 & 1 & 0.5 & 0.5 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.5 & 0.5 & 0.5 & 1 & 0.5 & 0.25 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.5 & 0.75 & 0.5 & 0.5 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.25 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Notice that the elements of matrix α are intentionally restricted to the set $\{0, 0.25, 0.5, 0.75, 1\}$ to maintain simplicity. The following mapping is defined between the set values and correlation level:

- **No Correlation:** denoted by the value 0 , it is used to describe the relationship between two techniques that do not share a common stimulus or activity
- **Low Correlation:** denoted by the value 0.25
- **Moderate Correlation:** denoted by the value 0.5
- **High Correlation:** denoted by the value 0.75
- **Perfect Correlation:** denoted by the value 1 , it represents the correlation between two identical techniques

Various relaxation techniques are appropriate for different contexts. For instance, napping is not a valid relaxation technique when the user is at work. Hence, we consider a list of predefined contexts, where context is limited in our evaluation to the geographical location of the user:

- | | |
|---------|----------|
| 1. Work | 4. Class |
| 2. Home | 5. Gym |
| 3. Car | 6. Spa |

Consequently, E becomes a 6×15 matrix describing the appropriateness of a relaxation technique for a particular context (i.e. location of user). For instance the element at row 1 and column 13 allocates a weight of 0.5 to eating at work. While row 3 and column 2 allocates a weight of 0 to watching relaxing images while driving. An example of the E matrix is provided below:

$$E = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0.5 & 0 & 0 & 0.5 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 1 & 1 & 1 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0.5 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.25 & 0 & 0 & 0.25 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0.25 & 0.25 & 0.25 & 0.25 & 0.25 & 0 & 0 & 0 & 0 & 1 \\ 0.75 & 0.75 & 0.75 & 0.75 & 0.75 & 0.25 & 0.25 & 0.25 & 0.5 & 0.5 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

The values of matrix E also belong to the set $\{0, 0.25, 0.5, 0.75, 1\}$. A value of 0 in E refers to a completely inappropriate relaxation technique for a given context. In contrast, a value of 1 denotes an ideal technique for a context. The other entries of the set denote an appropriateness level between the aforementioned two extremes that is relative to their value.

5.5.1.2 Simulation Results

In order to investigate the correctness of our mathematical model, a simulation was performed. The simulation makes use of the above described setting. For the purpose of validating the model, in this simulation, the physiological responses denoted by the variable $p_i[t]$ (see Equation (4.11)) and the context $c[t]$ are not measured or retrieved, they are rather predefined. The focus of this simulation is the evaluation of the mathematical model that personalizes the relaxation process, rather than the assessment of a stress management system as a whole.

We present the following scenario, where the user supplies a list of preferences for the various supported relaxation techniques. This is represented by matrix X below (or Table 5.9).

$$X = [10 \ 5 \ 8 \ 2 \ 3 \ 0 \ 0 \ 0 \ 0 \ 5 \ 0 \ 0 \ 0 \ 0 \ 0]$$

Also, Table 5.10 supplies the predefined signals of $p_i[t]$ and $c[t]$. These signals are usually measured or deduced automatically in a stress management system.

Table 5.9 List of Relaxation Preferences

Relaxing music	10
Relaxing images	5
Relaxing images and music	8
Peaceful sounds	2

Relaxing images and peaceful sounds	3
Visualization meditation	0
Deep breathing meditation	0
Body scan meditation	0
Progressive muscle relaxation	0
Breathing exercise	5
Massage	0
Funny videos	0
Eating	0
Napping	0
Exercising	0

Table 5.10 Predefined $p_i[t]$ and $c[t]$ signals

t	0	1	2	3	4	5	6	7	8	9	10
$p_i[t]$	N/A	-0.25	-0.35	-0.25	0.15	-0.12	0.33	0.1	0.4	0.55	0.35
$c[t]$	1	1	1	1	3	2	2	2	5	5	5

Figure 5.13 shows the evolved relaxation preference matrix W with respect to the time variable t . In this simulation, the context is not taken into account. For every iteration, the technique corresponding to the maximum value of W is recommended to the user. At the beginning, the relaxing music technique is given the highest precedence. This is directly retrieved from the original user preference (i.e. matrix X). Nonetheless, that relaxation technique performs negatively (since $p_1[1] = -0.25$). Therefore, at the end of the iteration (at $t=1$), the mathematical model disadvantages that relaxation technique along with highly correlated ones (such as relaxing music with images) in the resulting evolved preference matrix. Conversely, other non-correlated relaxation techniques (e.g. breathing exercise) are given a boost as they might be considered good alternatives in the future. As the relaxing music technique continue to produce poor results, it is overtaken by the breathing exercise at $t=3$. That technique's preference is continuously boosted throughout the remainder of the simulation as it continues to produce good results as evidenced in the values of $p_i[t]$ for $t > 3$ in Table 5.10.

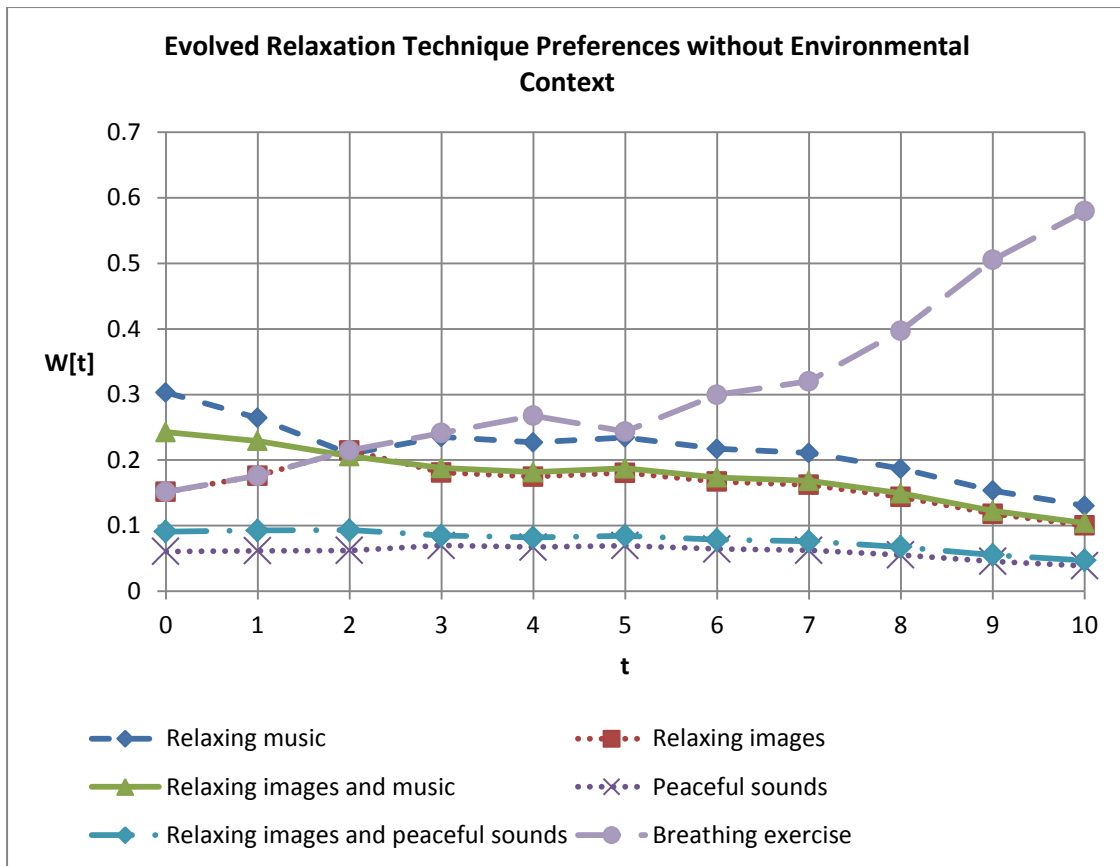


Fig. 5.13 Evolved Relaxation Technique Preferences without Environmental Context

Figure 5.14 shows the evolved probability mass function $F[i,t]$ when the context is taken into account in the evolution of the user's preference. At the beginning, the user is at work ($c[0] = 1$). Since listening to relaxing music is deemed appropriate for work and it is the preferred method of relaxation to the user, it is given the highest preference at $t = 0$. This technique produces a string of negative results for $1 \leq t \leq 3$, yet it is still given precedence given the context of the user (work and car) where the competing method, breathing exercise, is not deemed the most appropriate according to matrix E . As the user reaches home starting at $t = 5$, the breathing exercise preference is boosted. Nonetheless, towards the end of the simulation at $t = 8$, the user goes to the gym, and again, the relaxing music is deemed the most appropriate technique. At this point, it produces a string of positive performance and its preference is continuously incremented.

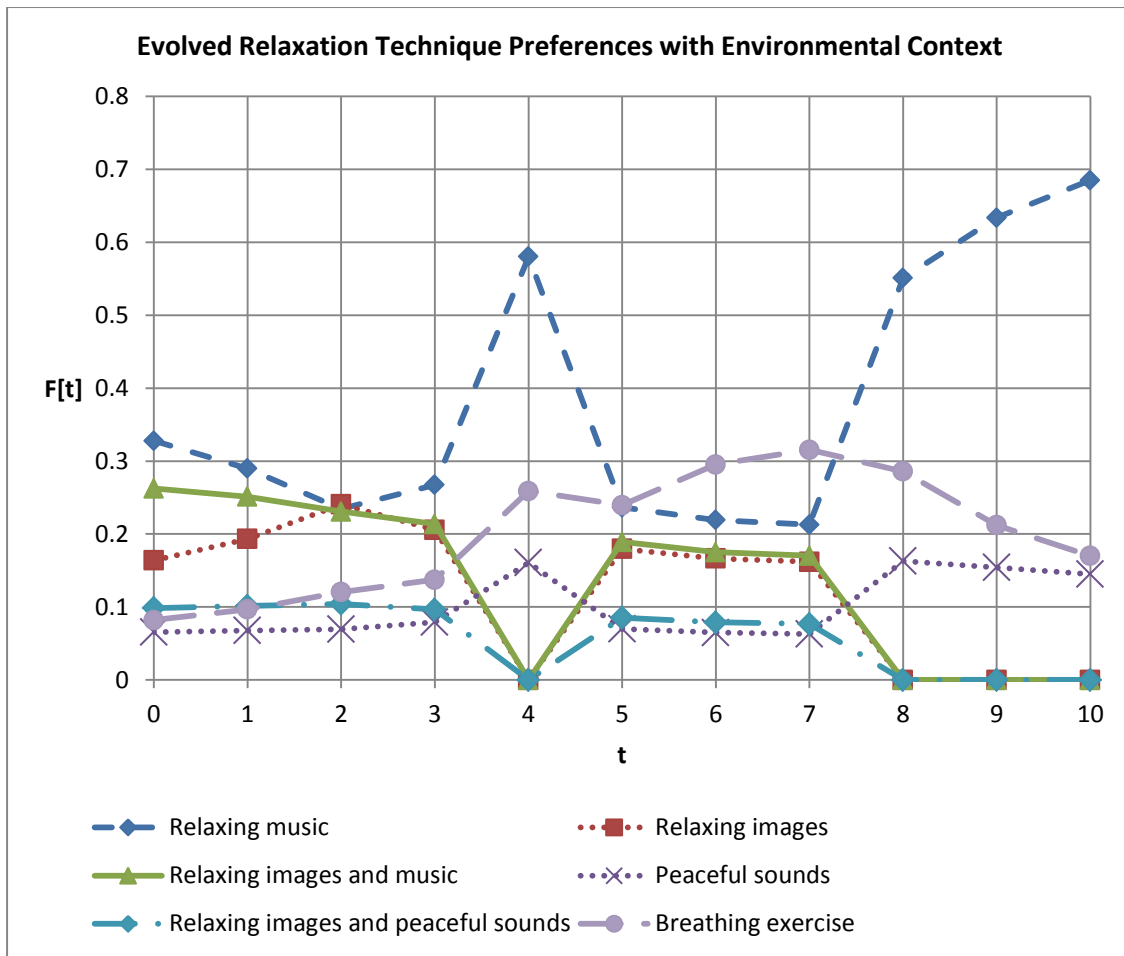


Fig. 5.14 Evolved Relaxation Technique Preferences with Environmental Context

5.5.2 Personalization with U-Biofeedback System

5.5.2.1 Personalized Relaxation Assistant (PRA)

In order to evaluate the effects of relaxation personalization on individuals using a U-Biofeedback system, we updated the Relaxation Assistant application used with the Biofeedback Serious Game presented in this Chapter to support personalization. The personalization is implemented using the mathematical model presented in Chapter 4. We call the new application, the Personalized Relaxation Assistant (PRA). Figure 5.15 shows a high level overview of the new U-Biofeedback system. The BSG assesses the mental stress level and stores a Mental Stress Report (MSR) in the MSR DB every 30 seconds. The MSR contains a timestamp, the latest calculated HRV parameters (LF, HF, LF/HF, HR and SDNN)

and a Stress Index (computed using Equation 4.4) associated with these parameters. Whenever an Acute Stress situation is detected, the BSG sends a corresponding event to the PRA which in turn guides the user through the appropriate relaxation technique (computed using the Personalization Mathematical Model). The following relaxation responses are provided by the PRA:

- A slideshow of relaxing images with the following options:
 - Accompanied by relaxing music
 - Accompanied by peaceful sounds
 - Without audio stimulus
- A list of suggested short comedy videos that the user can play
- A list of Breathing Exercises instructional videos
- A list of Guided Meditation instructional videos
- A list of Progressive Muscle Relaxation instructional videos

In the case of the relaxing images slide show, the images are randomly loaded from a large local database of preselected content (more than two thousand images). These images display scenes of nature and are routinely used for such purpose. The same applies for music (78 pieces), peaceful sounds (17 audio clips), breathing exercises (9 videos), guided meditation (15 videos) and progressive muscle relaxation (5 scripts). The aforementioned media content stored in the local database is large enough so that it does not repeat frequently for one technique (at least in most cases). Although it might be beneficial to repeat the same Breathing Exercise, Guided Meditation and Progressive Muscle Relaxation videos as the user becomes more familiar with these processes, we opted to preserve an element of newness every time one of these relaxation techniques is suggested in order to maintain the interest of the participant. Furthermore, most of the videos associated with these techniques convey fairly similar material, just presented slightly differently. The list of suggested comedy videos

is randomly generated chosen and streamed from the YouTube servers. In this case, strict filters have been applied to the queries sent to YouTube to ensure that no inappropriate content is selected. Also, the content is limited to a set of well-known and trusted authors.

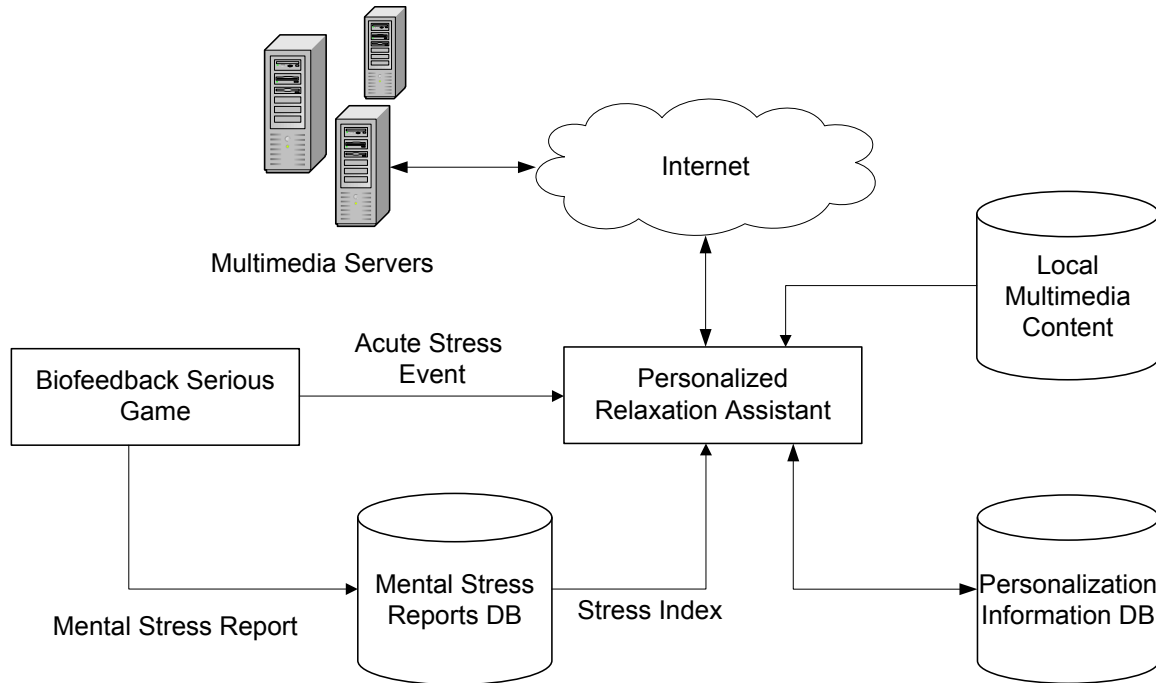


Fig. 5.15 Updated U-Biofeedback System Architecture

Whenever a relaxation technique is consumed through the PRA, a Performance Index is calculated using Equation (5.4):

$$p_i[t] = \begin{cases} 1, & f[t] > 1 \\ f[t], & -1 \leq f[t] \leq 1 \\ -1, & f[t] < -1 \end{cases} \quad (5.4)$$

Where $f[t]$ is the Stress Index computed using Equation (4.4). The Evolved Relaxation Preferences Matrix W is then calculated using the Performance Index (see Equations (5.1) and (5.2)) and stored in the Personalization Information Database. The geographical context was not taken into account in this application.

5.5.2.2 Evaluation of the Personalized Relaxation Assistant

In order to evaluate the effects of relaxation personalization in a U-Biofeedback system, we conducted an experiment over a period of 47 days on 2 consenting adult subjects:

- **Subject 1:** 27 years old male software developer
- **Subject 2:** 23 years old female student

The subjects used the system mainly while working or studying. On average, the system was used for 96 minutes per day by Subject 1 and 126 minutes per day by subject 2. The experiment was interrupted for 15 days for Subject 1 due to a sensor malfunction. Nonetheless, we do not believe this interruption had any bearing on the overall results.

We have configured the PRA to alternate the application of personalization. This means that it provides personalized recommendations only every second time. The rest of the instances, the Personalization Engine suggests a default relaxation technique: breathing exercise instructional videos. Therefore, the first time the PRA is executed, it offers the default technique. The second time, it recommends a technique based on the output of the personalization mathematical model, and so forth. We told the subjects that if they decide to start the relaxation process based on the advice of the system, they have to keep it running for at least 5 minutes and up to a maximum of 15 minutes. Otherwise, they can just decline to start it. The subjects were not informed of the alternation between personalization and “no personalization”. They were just simply told that the PRA would recommend relaxation techniques that should help them diffuse stressful situations.

We have kept the experiment running until the system identified 14 acute stress events for each subjects. Table 5.11 summarizes the amount of time (in seconds) each subject kept the relaxation assistant application running. A running time of zero means that the subject decided not to run the relaxation process. Table 5.12 shows the Stress Index after starting (or declining to start) the PRA. The Stress Index was computed using Equation (4.4). Note that a negative Stress Index implies more stress compared to the benchmark condition. On the other hand, a positive Stress Index implies a more relaxed state than the benchmark.

In Table 5.11, we see that on average, the first subject spent 15.95% longer running the relaxation process when personalization was applied (compared to no personalization). Similarly, the second subject spent 31.43% longer consuming personalized relaxation contents (compared to non-personalized contents). In Table 5.12, we see that on average, the Stress Index improved by 72.97% for subject 1 and 240.34% for subject 2 when personalization was employed (compared to no personalization). The latter high percentages are caused by the negative Stress Index values registered many instances (3 times for each subject) when the subjects declined to start the relaxation process for non-personalized suggestions. Therefore, based on these results, we deem that the subjects were more interested in undergoing relaxation when personalization was applied. By increasing the likelihood of relaxation utilization, or prolonging the duration of relaxation consumption, we deduce that personalization can considerably increase the effectiveness of a U-Biofeedback stress management solution.

Table 5.11 Time Spent Performing Relaxation after every Acute Stress Event

Time Spent Running Personalized Relaxation Assistant (in Seconds)					
Without Personalization			With Personalization		
Instance	Subject 1	Subject 2	Instance	Subject 1	Subject 2
1	876	900	2	715	716
3	726	890	4	326	845
5	0	0	6	0	426
7	785	0	8	715	471
9	309	769	10	426	793
11	0	0	12	629	421
13	0	900	14	315	874
Average	385.14	494.14	Average	446.57	649.43
STDEV	401.62	464.44	STDEV	261.11	203.17

Table 5.12 Stress Index after Running (or Declining to Run) the PRA

Stress Index After Running (or Refusing to Run) the PRA					
Without Personalization			With Personalization		
Instance	Subject 1	Subject 2	Instance	Subject 1	Subject 2
1	0.62	0.67	2	0.66	0.42
3	0.71	0.78	4	0.21	0.86
5	-0.15	-0.36	6	-0.14	0.42
7	0	-0.27	8	0.32	0.36
9	0.2	-0.1	10	0.15	0.58
11	-0.11	-0.34	12	0.41	0.5
13	-0.16	0.81	14	0.31	0.91
Average	0.16	0.17	Average	0.27	0.58
STDEV	0.37	0.55	STDEV	0.25	0.22

6 Heart Rate Variability Artifact Correction

In order to accurately analyse stress situations in the context of a U-Biofeedback Stress Management system, artifact plagued HRV signals must be preprocessed in order to eliminate such erroneous data points. This step would minimize the effect of the artifacts on the integrity of the measured signal. In this Chapter we will discuss several algorithms used to that end and compare them to our proposed algorithms.

6.1 Artifact Filtration

Canceling the effects of artifacts on time and frequency domain HRV analysis is performed in two stages. In the first stage, the Artifact Detection, a list of all the artifacts in an HRV signal is compiled. In the second stage, the Artifact Correction, the effect of the artifacts is rectified using one of three operations: insertion, deletion and interpolation of sample(s) (see Figure 6.1). Details regarding the context of the latter operations will be provided later in this Section 6.5.

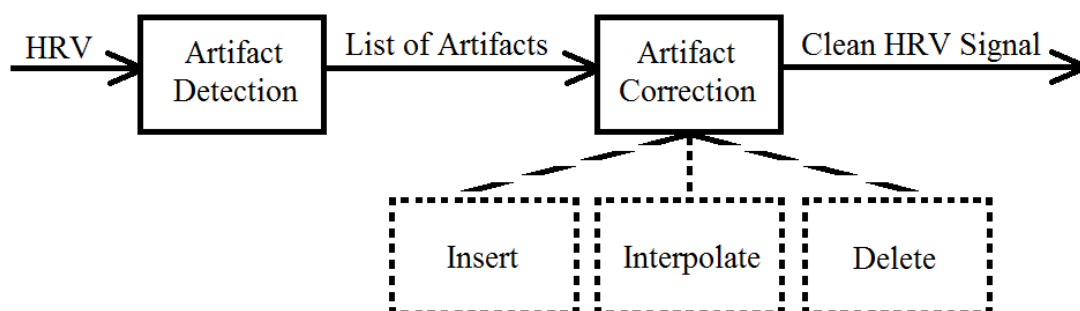


Fig. 6.1 HRV Artifact Filtration Process

6.2 Categories of Artifacts

To better understand the causes of artifacts, whether they have a physiological or a measurement source, the next three sections divide these artifacts into three categories and

provide an overview of their origins. The categories are formed according to how they are manifested in an HRV record, rather than their source. For instance, an interruption in the measurement or a QRS miss by the R-peak detection algorithm produce a similar HRV structure, and therefore these artifacts belong to the same category. But before we introduce the three categories of artifacts, we must define the following parameters:

$$I_1 = X(a) \tag{6.1}$$

$$I_2 = X(a + 1) \tag{6.2}$$

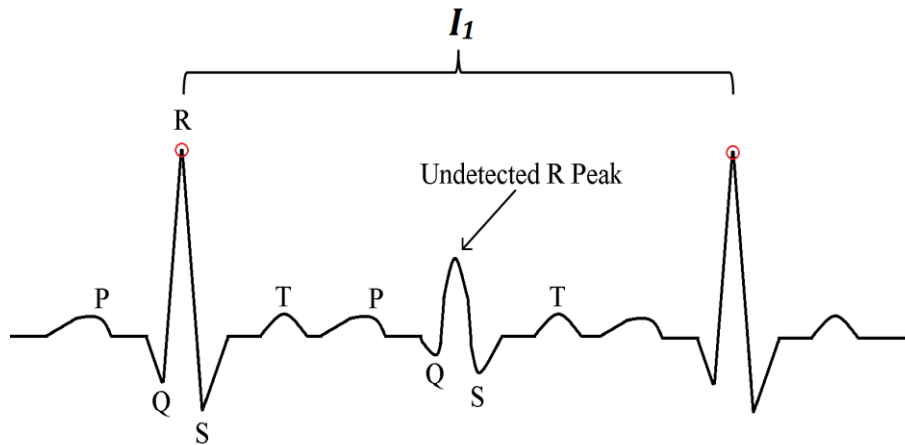
$$I_3 = X(a) + X(a + 1) \tag{6.3}$$

$$\bar{X} = \frac{\sum_{i=1}^N X(i)}{N} \tag{6.4}$$

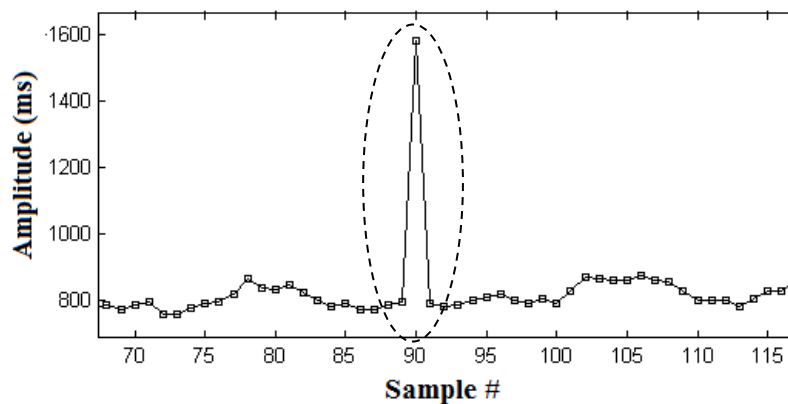
Where $X(i)$ is the HRV signal, a is the index of the artifact and N is the number of samples in the HRV record.

6.2.1 Category 1

In the HRV record, this category of artifacts is manifested as an upward peaking impulse composed of a single data point. This can be caused by an interruption of measurement or a miss of a QRS complex by the R-peak detection algorithm. Therefore, an interpolation is required to estimate the location of the undetected or unmeasured R-peak(s). Achieving such outcome by manipulating the HRV signal consists of removing the data point causing the impulse and replacing it with a sequence of interpolated ones. Figure 6.2 displays a category 1 artifact, along with its manifestation in the ECG and HRV signals. Note that the dashed circle indicates the presence of the artifact.



A) ECG Manifestation



B) HRV Manifestation

Fig. 6.2 Category 1 Artifact in the ECG and HRV Signals

6.2.2 Category 2

These artifacts are manifested as a downward peaking impulse composed of two data points (see Figure 6.3B). The cause of such structure might be an ectopic beat mistaken for a normal one or an ECG feature (such as a T wave) incorrectly identified as an R peak.

In the case of an ectopic beat, the extra contraction causes the heart timing to restart and therefore, after a short delay, fire again from the SA node. This produces strangely spaced normal beats with an ectopic beat in between (see Figure 6.3A). The interval between the two normal beats (I_3) is noticeably smaller than two times the average interval between consecutive normal R-peaks ($2 \times \bar{X}$). On the other hand, I_3 is in most cases noticeably larger than \bar{X} . This produces a downward peaking impulse because the interval between the first

normal beat and the ectopic beat (I_1) is noticeably smaller than \bar{X} . Likewise, the interval between the ectopic beat and the second normal beat (I_2) is also noticeably smaller than \bar{X} . In the case of an incorrectly detected R-peak between two normal R peaks, I_3 is usually in the vicinity of \bar{X} .

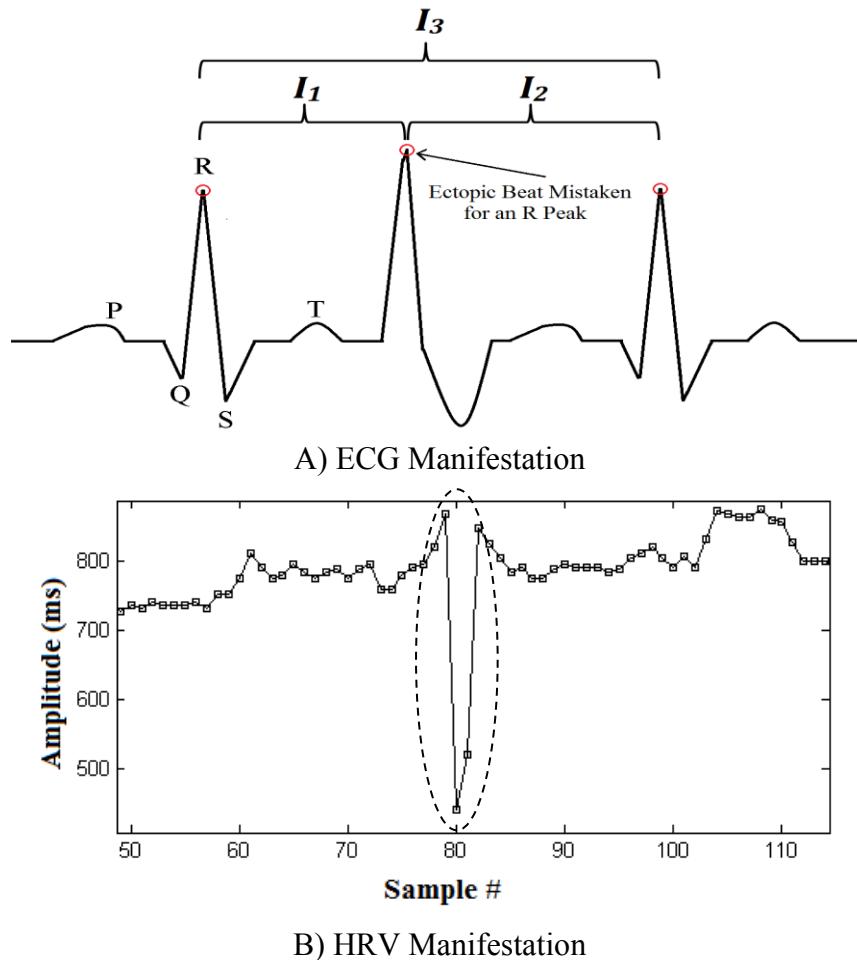
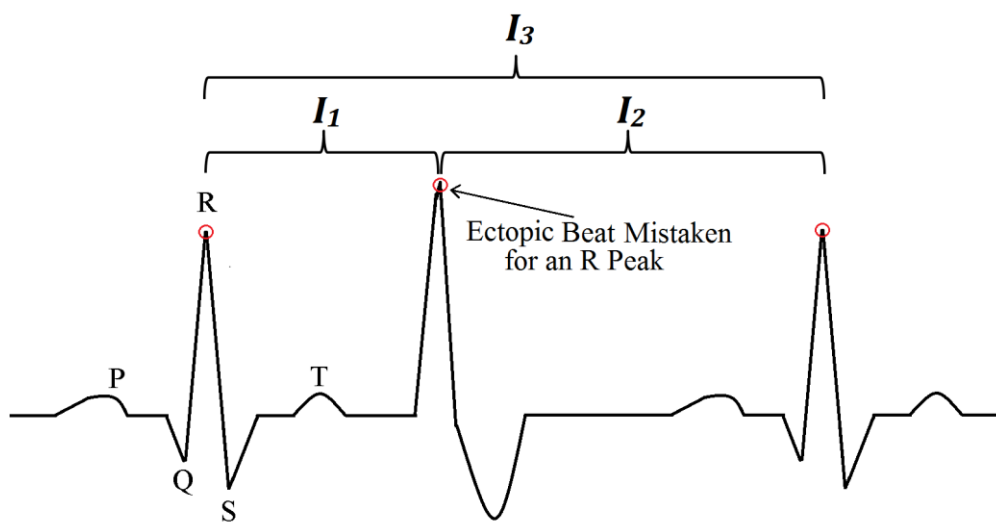


Fig. 6.3 Category 2 Artifact in the ECG and HRV Signals

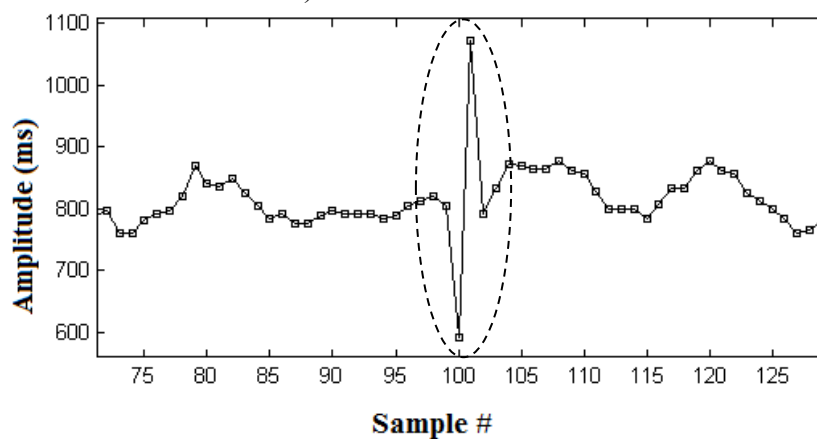
6.2.3 Category 3

These artifacts exhibit a downward peaking impulse composed of one data point followed by an upward peaking impulse composed of one data point as well (see Figure 6.4B). Such structure is almost exclusively caused by an ectopic beat. In this case, the ectopic beat prevents the normal one from taking place and therefore the heart skips a normal beat. The next normal beat usually comes right when it would have arrived had the ectopic episode not

occurred (see Figure 6.4A). In this case, the interval between the two normal beats surrounding the ectopic beat is almost two times the average of all RR intervals ($I_3 \approx 2 \times \bar{X}$). This results in a downward peaking impulse caused by the unusually small interval between the normal beat and the ectopic one (I_1), followed by an upward peaking impulse caused by the unusually long interval between the ectopic beat and the next normal beat (I_2). Therefore, in this case the interpolation algorithm must replace the two erroneous HRV data points with two interpolated ones.



A) ECG Manifestation



B) HRV Manifestation

Fig. 6.4 Category 3 Artifact in the ECG and HRV Signals

6.3 Existing Artifact Detection Algorithms

In this Section we will present four existing algorithms for detecting artifacts in HRV signals. In the next Section, we will introduce two of our own methods that extend the Impulse Rejection filter presented in [55] and discussed later in this Section.

6.3.1 Simple Thresholding (ST) Algorithm

Perhaps the most basic algorithm to identify artifacts in an HRV signal makes use of an upper and lower threshold [57, 52]. The idea is that normal heart rate is limited in range and therefore, detecting HRV samples that violate such paradigm indicates the presence of an artifact. This is formalized using Equation (6.5):

$$S(i) = \begin{cases} X(i), & R_1 \leq X(i) \leq R_2 \\ \text{Correct}\{X(i)\}, & \text{Otherwise} \end{cases} \quad (6.5)$$

Where $S(i)$ is the resulting filtered HRV signal, R_1 and R_2 are the upper and lower thresholds respectively. The algorithm of [52] uses a value of 300 ms for R_1 and 1800 ms for R_2 .

6.3.2 Moving Average (MA) Algorithm

This algorithm is based on the work presented in [54]. For each sample, a window containing the previous 30 seconds of HRV data points is averaged to produce an Expected Inter Beat Interval (EIBI) value for each HRV sample. The EIBI series is therefore calculated using Equation (6.6) where n represents the previous 30 seconds worth of HRV samples (i.e. $\sum_{j=i-n}^i X(j) = 30000 \text{ ms}$).

$$EIBI(i) = \frac{\sum_{j=i-n}^i X(j)}{n} \quad (6.6)$$

Then, an erroneous sample is detected and corrected using the following test:

$$s(i) = \begin{cases} X(i), & \theta \times EIBI(i) \leq X(i) \leq \alpha \times EIBI(i) \\ \text{Correct}\{X(i)\}, & \text{Otherwise} \end{cases} \quad (6.7)$$

where $\alpha \in]1, \infty[$ and $\theta \in]0, 1[$. In [54], α is set to 2 and θ to 0.6. The idea behind this algorithm is simple; each new sample must be somewhat similar to a window of samples that preceded it. If a sample is therefore found to be significantly different than its predecessors, it is judged to be erroneous and therefore corrected.

On the other hand, a special arrangement has to be made for the first 30 seconds of the record, as there are not enough samples that precede them to fill a window. These particular samples can be tested against the EIBI value produced from the first window in the record.

6.3.3 Integral Pulse Frequency Modulation (IPFM) Algorithm

This algorithm is presented in [56] and uses the Integral Pulse Frequency Modulation (IPFM) model to detect ectopic beats. IPFM has been considered to describe the behavior of the ANS in controlling the heart rate [56]. At the root of this model is the modulating signal $m(t)$ that replicates the sympathetic and parasympathetic influences on the firing of the SA node [73]. Therefore, a heartbeat is generated when the integral of Equation (6.8) reaches a threshold Ψ :

$$\Psi = \int_{t_i}^{t_{i+1}} m(t) dt \quad (6.8)$$

Where t_i is the time of the previous beat and t_{i+1} is the time of the new beat. The modulating function $m(t)$ is composed of a DC component m_0 and an dynamic component $m_1(t)$. Similarly, such phenomenon can be represented by the block diagram of Figure 6.5 [74].

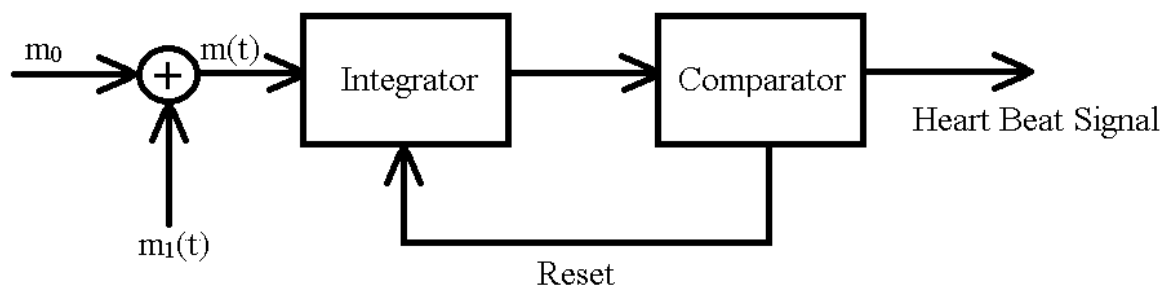


Fig. 6.5 IPFM Model [74]

Now [56] exploits the fact that the variation in the instantaneous heart rate due to non-ectopic beats is band limited according to the IPFM model. Therefore, using a thresholding test on the derivative of the instantaneous heart rate, ectopic beats can be detected (as ectopic beats cause a faster change in the instantaneous heart rate than normal ones). The instantaneous heart rate derivative is estimated using Equation (6.9).

$$I'_k = 2 \left| \frac{t_{k-1} - 2t_k + t_{k+1}}{(t_{k-1} - t_k)(t_{k-1} - t_{k+1})(t_k - t_{k+1})} \right| < U\sigma \quad (6.9)$$

Where I'_k represents the derivative of the instantaneous heart rate, t_k is the time of the k^{th} heart beat, U is a predefined threshold and σ is the standard deviation of the HRV signal. Therefore, a beat is considered non-ectopic when the derivative of the instantaneous heart rate (I'_k) is bigger than the threshold (U). The authors of [56] proposed to use a value of U that is 4.3 times the standard deviation of the HRV signal.

6.3.4 Impulse Rejection (IR) Filter Algorithm

This algorithm is presented in [55]. It makes use of an impulse rejection filter that uses the median function to detect any possible HRV artifacts. The following test statistic is employed,

$$d(i) = \frac{|X(i) - Xm|}{1.483 \times \text{med}\{|X(i) - Xm|\}} \quad (6.10)$$

Where $\text{med}\{\cdot\}$ is the median operator applied over the entire record of $|X(i) - Xm|$ and Xm is the median of $X(i)$. The filtered signal is then calculated as:

$$S(i) = \begin{cases} X(i), & d(i) < \phi \\ \text{Correct}\{X(i)\}, & d(i) \geq \phi \end{cases} \quad (6.11)$$

Where $S(i)$ is the resulting filtered HRV signal and ϕ is a pre-defined threshold. In the tests performed in [55], the value of ϕ was set to 4.

6.4 Proposed Artifact Detection Algorithms

In this Section, we discuss two proposed artifact detection algorithms. The first one extends the IR algorithm by introducing the concept of windowing. The second uses windowing as well, but also examines the patterns formed by sequences of HRV samples in its investigation.

6.4.1 Windowed Impulse Rejection (WIR) Filter Algorithm

One of the problems in the previous algorithm (IR) is that it is not sensitive to major changes in the heart rate. It examines the record as a whole without segmentation. Many ECG sensors are wearable and therefore monitor the heart's behavior while the user performs various activities. An example of such application is an ECG monitor that an athlete might wear during exercising to collect her or his heart rate and HRV parameters. During such activities, the heart rate tends to change considerably. Nonetheless, such drastic changes in the heart rate in a short time span are not accounted for in the previous algorithm as will see in the evaluation (Section 6.7.1).

The aforementioned weakness can be overcome using a windowed approach that segments the record into small portions. In fact, [55] proposes windowing for long records (with each window containing at least 5 minutes worth of samples). Nonetheless, we propose the use of small overlapping windows to account for the potential dynamic nature of the HRV signal. The motivation for overlapping the windows is to take into regard a signal's continuous nature. It would be disadvantageous to treat adjacent windows completely independently while in reality one is a continuation of the other. Using Equations (6.12) and (6.13), the number of windows needed to filter the signal is calculated:

$$d = [\omega \times (1-\alpha)] \tag{6.12}$$

$$l = \left\lceil \frac{(N-\omega)}{d} \right\rceil + 1 \tag{6.13}$$

Where α is the overlap factor that has the range $0.5 \leq \alpha < 1$ (for an overlap of at least 50%), ω is the window length, N is the total number of samples in the signal and l is the number of windows. This guarantees that every sample is tested at least twice with regards to its surroundings in order to judge whether it is an artifact, (except for the first d samples that are tested only once). We define $W_j(i)$ as the content of the j^{th} window with the first element corresponding to $X(j \times d)$ and the last element corresponding to $X((j \times d) + \omega)$.

For each window, the following signal is calculated:

$$P_j(i) = \frac{W_j(i) - Wm_j}{\text{med}\{|W_j(i) - Wm_j|\}} \quad (6.14)$$

Where $1 \leq i \leq \omega$, $\text{med}\{.\}$ is the median operator applied over the entire record of $|W_j(i) - Wm_j|$ and Wm_j is the median of $W_j(i)$. The filtered signal is therefore calculated using the following equation:

$$S((j \times d) + i) = \begin{cases} W_j(i), & |P_j(i)| < T \\ \text{Correct}\{W_j(i)\}, & |P_j(i)| \geq T \end{cases} \quad (6.15)$$

Where $S(i)$ is the resulting filtered HRV signal. In this work, α was set to 0.5 and ω to 90.

6.4.2 Pattern Based Windowed Impulse Rejection (PWIR) Filter Algorithm

This technique is very similar to the previous one and makes use mostly of the same Equations; nonetheless, we also examine the patterns formed by sequences of samples to assess whether they match any of the artifact categories discussed in Section 6.2. Therefore, the procedure works as follows:

1. Consider every sample $X(i)$ being evaluated to be an artifact (until proven otherwise) and test for its potential category. The latter can be achieved through the tests described in Table 6.1:

Table 6.1 Tests to Assess the Category of the Potential Artifact

Category Test	Potential Category
$m_1(i) > 0$ AND $m_2(i) < 0$	1
$m_1(i) < 0$ AND $m_3(i) > 0$	2
$m_1(i) < 0$ AND $m_2(i) > 0$ AND $m_3(i) < 0$	3

Where $m_k(i)$ (for $0 \leq k \leq 2$) is calculated using Equation (6.16).

$$m_k(i) = P_j(i+k) - P_j(i-1+k) \quad (6.16)$$

2. If the sample, along with its surroundings, forms a structure resembling one of the artifact categories, then perform the corresponding test in Table 6.2 to verify if the sample is an erroneous one and therefore should be corrected.

Table 6.2 Customized Artifact Tests for Each Category

Category	Condition for Correction
1	$ m_1(i) > T_1$ AND $ m_2(i) > T_1$
2	$ m_1(i) > T_2$ AND $ m_3(i) > T_2$
3	$ m_2(i) > T_3$ AND ($ m_1(i) > T_3$ OR $ m_2(i) > T_3$)

In Table 6.2, the T_1 , T_2 and T_3 thresholds are positive constants. By checking for patterns and impulses, rather than just impulses in a window, we can set much stricter threshold values without worrying about increasing the rate of false detections (i.e. reaching the false conclusion that a valid sample is an artifact). Hence, we are not only looking for sudden jumps in the HRV signal, but also at the shape formed by every consecutive 4 samples in the signal.

6.5 Artifact Correction

All artifact detection techniques listed above provide conditions for sample correction. In other words, when a sample is judged to be an artifact, correctional measures are taken. Nonetheless, these measures depend on the nature of the artifact. Table 6.3 provides a description of the corrective measures that should be undertaken to correct artifacts belonging to the three categories previously defined.

Table 6.3 Correction Actions for Various Types of Artifacts

Category	Condition	Cause	Corrective Action
1	a) $X(a) > 2.5 \times \bar{X}$	An interruption in measurement occurred.	The HRV record can no longer be treated as a contiguous record in any analysis exercise. The value I_3 indicates the length of the interruption period.
	b) $X(a) \leq 2.5 \times \bar{X}$	It is likely that $X(a)$ was produced by QRS detection miss.	Interpolate two HRV samples to replace $X(a)$ and $X(a+1)$
2	a) $I_3 \approx \bar{X}$	An ECG component (likely a T wave) was mistaken for an R peak.	Replace $X(a)$ and $X(a+1)$ by I_3 .
	b) $\bar{X} \ll I_3 \ll 2 \times \bar{X}$	Ectopic beat	Interpolate two HRV samples to replace $X(a)$ and $X(a+1)$
3	All occurrences of this category	Ectopic beat	Interpolate two HRV samples to replace $X(a)$ and $X(a+1)$.

6.6 Interpolation

Interpolation techniques are means to replace artifacts with new data points that are ideally equal in value to the samples that would have registered had the artifacts not occurred. Unfortunately, this ideal scenario is impossible to realize. Nonetheless, estimating these samples by applying a mathematical equation on the surrounding points will yield good

results, especially that sudden heart rate changes do not occur instantaneously (at least according to the IPFM model [56]).

6.6.1 Existing Interpolation Techniques

In this Section, we will review some of the common interpolation techniques to replace artifacts in an HRV signal.

6.6.1.1 Median Interpolation

A mechanism for interpolating artifacts is proposed by [55] and uses Equation (6.17).

$$\hat{X}(a) = \text{med}\{W_m(i)\} \quad (6.17)$$

Where $\hat{X}(a)$ is the newly interpolated value, $W_m(i)$ is a window that corresponds to the HRV samples between $X(a - \frac{\omega-1}{2})$ and $X(a + \frac{\omega-1}{2})$ and ω is the length of the window. In [55], a window of size 5 ($\omega = 5$) was used.

6.6.1.2 Linear Interpolation

Perhaps the simplest method to perform interpolation is through a linear function. Some small portions of the HRV signal (composed of few contiguous data points) display a somewhat linear behavior. This is especially true for HRV signals collected during normal or fast breathing. Slow breathing rates tend to increase the low frequency and decrease high frequency components [75] and consequently creating a less linear and more “curvy” signal. However, this method provides simplicity in implementation and calculation. The interpolated sample is calculated using Equation (6.18):

$$\hat{X}(a) = \frac{X(a-1)+X(a+c)}{2} \quad (6.18)$$

Where $\hat{X}(a)$ is the newly interpolated value, a is the index of the sample to be interpolated and c is the number of consecutive artifacts starting at $X(a)$.

6.6.1.3 Cardinal Cubic Spline Interpolation

The following method is based on the cardinal splines interpolation, which in turn is based on the more generic hermite interpolation. First, the four hermite basis functions are calculated using the following equations:

$$h_1(s) = 2s^3 - 3s^2 + 1 \quad (6.19)$$

$$h_2(s) = -2s^3 + 3s^2 \quad (6.20)$$

$$h_3(s) = s^3 - 2s^2 + s \quad (6.21)$$

$$h_4(s) = s^3 - s^2 \quad (6.22)$$

The value of s is calculated as follows:

$$s = \frac{i_c}{c+1} \quad (6.23)$$

Where c is the total number of consecutive points to be interpolated starting at $X(a)$ and i_c is the index in the latter string of artifacts. Therefore, $i_c \in [1, c]$.

Using the previously defined formulas, we can calculate an interpolated point using Equation (6.24)

$$\hat{X}(a) = h_1 \times X(a-1) + h_2 \times X(a+c) + h_3 \times T_1 + h_4 \times T_2 \quad (6.24)$$

T_1 and T_2 are the tangents at $X(a-1)$ and $X(a+c)$ and can be estimated using Equations (6.25) and (6.26).

$$T_1 = \frac{X(a+c) - X(a-2)}{2} \quad (6.25)$$

$$T_2 = \frac{X(a+c+1) - X(a-1)}{2} \quad (6.26)$$

6.6.1.4 Nonlinear Predictive Interpolation

Lippman, Stein and Lerman use a Predictive Interpolation method to replace erroneous data points [80]. In their algorithm, a sequence of m samples before and n samples after the sequence of ectopic beats is defined. This operation results in a sequence of $m+c+n$ samples (where c is the number of consecutive artifacts). We call this sequence the Original Template (OT) and is obtained as follows:

$$OT = X(a - m), \dots, X(a + c + n - 1) \quad (6.27)$$

Where a is the index of the first artifact. Now the middle c points must be replaced by b samples (where b is the number of interpolated points that must be inserted between $X(a-1)$ and $X(a+c)$). In order to do that, the m and n intervals from this sequence are compared with the m and n intervals from all other sequences of size $m+b+n$. Using the Cartesian distance metric, the closest matching sequence is found. This is called the Matched Template (MT). The mean of the latter sequence is adjusted so that it matches that of the m and n samples of the Original Template. Then, the b samples of the MT are inserted into HRV signal between $X(a)$ and $X(a+c)$ in place of the erroneous ones. The study of [80] sets both m and n to 3.

6.6.2 Proposed Interpolation Technique

We propose an interpolation technique based on a combination of the Cubic and Nonlinear Predictive Interpolation methods. We call the algorithm, Cubic Predictive Interpolation. The algorithm works as follows:

1. Apply the Cardinal Cubic Spline Interpolation to calculate the required samples (use the same method provided in Section 6.6.1.3)
2. Find the Matched Template (MT), as described in Section 6.6.1.4
3. Calculate $h_1(s)$, $h_2(s)$, $h_3(s)$ and $h_4(s)$ using the Equations (6.19), (6.20), (6.21) and (6.22). In this case, s is defined as:

$$s = \frac{i_b}{b+1} \quad (6.28)$$

Where b is the number of samples to be interpolated, i_b is the index over these samples (i.e. $i_b \in [1, b]$). Therefore, we can calculate the Cubic Trend (CT) of the MT as follows:

$$CT(i_b) = h_1 \times MT(i_b - 1) + h_2 \times MT(i_b + b) + h_3 \times T_1 + h_4 \times T_2 \quad (6.29)$$

T_1 and T_2 are the tangents at $MT(i_b-1)$ and $MT(i_b+c)$ and can be estimated using Equations (6.30) and (6.31):

$$T_1 = \frac{X(a+c) - X(a-2)}{2} \quad (6.30)$$

$$T_2 = \frac{X(a+c+1) - X(a-1)}{2} \quad (6.31)$$

4. Remove the cubic trend from the MT sequence by subtracting CT from MT. This produces the Detrended Matched Template (DMT).
5. Add the b samples of the DMT onto the ones interpolated in step 1

6.7 Evaluation

6.7.1 Artifact Detection Evaluation

6.7.1.1 Evaluation Data Set

We evaluated the above presented algorithms on 79 records containing at least one artifact randomly chosen from the MIT-BIH Normal Sinus Rhythm and Long-Term Databases on Physionet [76]. Each record is a 5 minutes segment taken from one of 25 long term ECG recordings. All records used were manually annotated (or automatically annotated but later visually verified) by experts for ectopic beats, unclassifiable beats and other potential artifacts. We looked in particular for the following types of annotations:

- Premature atrial contractions
- Supraventricular premature contractions
- Premature ventricular contractions
- Unclassifiable beats
- Isolated QRS-like artifacts
- Pauses in measurement

The above presented list compiles the most common types of non-pathological artifacts. The first three types refer to various ectopic beats and the latter three refer to non-ectopic artifacts. From the list of annotations accompanying each ECG record, an HRV signal is

produced that is calculated using the time stamps of the annotated normal beats and the other erroneous features listed above.

6.7.1.2 Finding the Optimal Thresholds

All of the artifact detection algorithms we have introduced in this Chapter include a test based on one or more threshold values in order to assess the correctness of a sample. Threshold values have been suggested by the works that proposed these algorithms (namely [52], [54], [55] and [56]). Nonetheless, we opted to find the optimal thresholds in order to achieve a fair comparison between these algorithms and our proposed ones. Consequently, we devised a universal Performance Indicator against which the effectiveness of threshold values will be determined. The Performance Indicator takes into account the rate of accurate detection of artifacts and the rate of false detections. False detections cause the correction of valid HRV samples, which negatively affects the signal's integrity. Good threshold values should balance both rates. Therefore, the Performance Indicator simply corresponds to the difference between the True Positive Detection Rate (TPDR) and False Positive Detection Rate (FPDR).

We ran the algorithms on our HRV data in batch mode, while modifying the threshold values for every single execution. For ST (see Equation 6.5), we tested every possible value for $0 \leq R_1 \leq 700$ and $700 \leq R_2 \leq 300$ (with a step size of 5). We found the optimal values for R_1 and R_2 to be 600 and 900 respectively, yielding a Performance Indicator value of 50.70%. For MA (see Equation 6.7), we tested all values for $0 \leq \theta \leq 1$ and $1 \leq \alpha \leq 3$ (with a step size of 0.05). We found the optimal values for θ and α to be 0.85 and 1.15 respectively, yielding a Performance Indicator value of 70.28%.

The proposed PWIR makes use of three thresholds, one for each category of artifacts. Nonetheless, from our preliminary tests, we noticed that the algorithm performs well when $T1 \approx T2 \approx T3 + 1.6$. Also, similarly, we found a window size of 60 to perform optimally for

PWIR and WIR and therefore ω was fixed to 60 (see Equations 6.12 and 6.13). Using this information, we reduced the amount of thresholds for these algorithms to one. This allows us to compare the PWIR and WIR more easily with IPFM and IR, both of which rely only on one threshold. We tested all values between 0.1 and 15 (with a step size of 0.1) to find the optimal threshold for algorithms PWIR, IPFM, IR and WIR. Figure 6.6 plots the Performance Indicator vs the Threshold for these algorithms. Therefore, the optimal threshold for each algorithm is associated with the peak data point on the plot for that algorithm. Table 6.4 summarizes the optimal thresholds for all discussed algorithms.

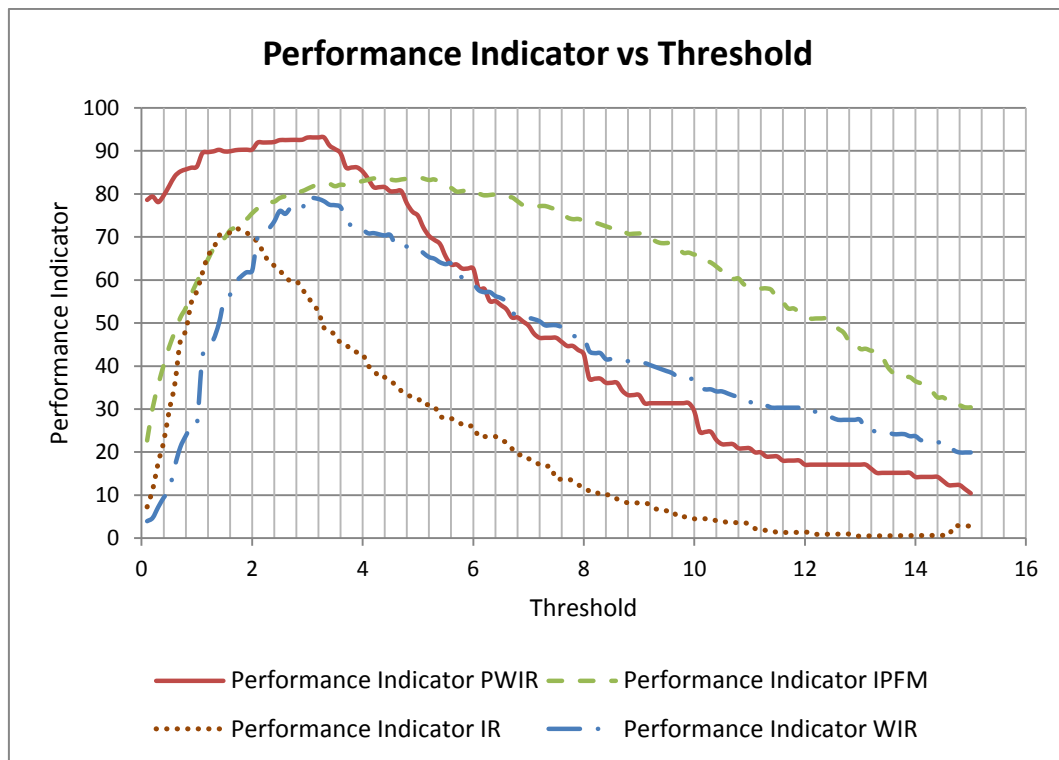


Fig. 6.6 Performance Indicator Plotted Against Possible Threshold Values

Table 6.4 Optimal Threshold Values for the IPFM, PWIR, WIR and IR Algorithms

Algorithm	Optimal Threshold(s)
IPFM	5.3
PWIR	3.3
WIR	3.0

IR	1.7
MA	0.85 and 1.15
ST	600 and 900

6.7.1.3 *Artifact Detection Results*

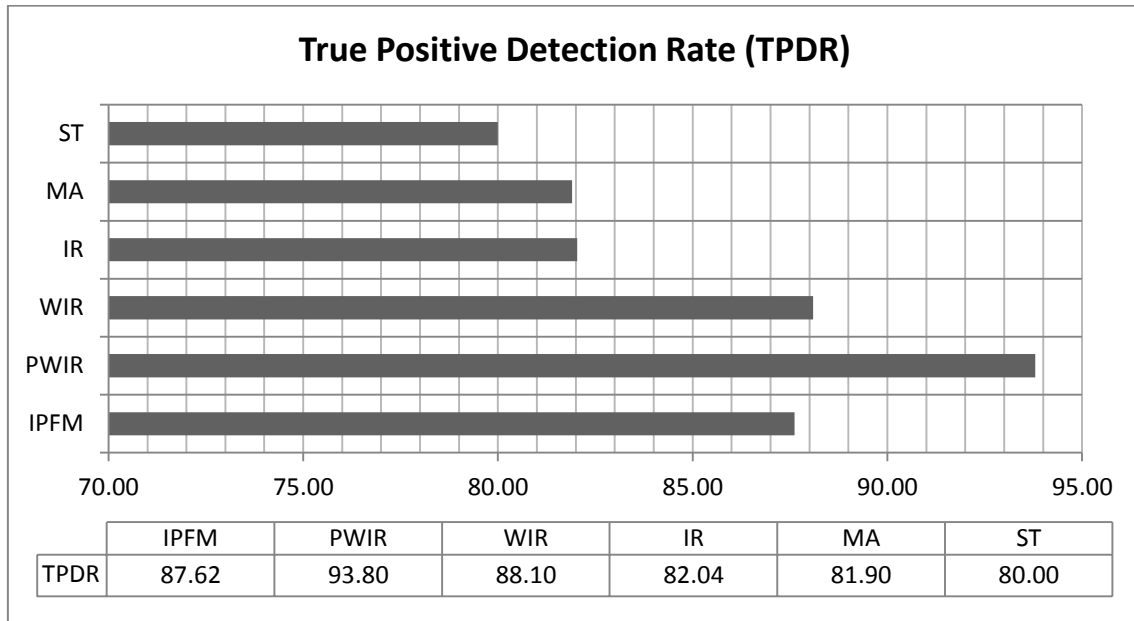


Fig. 6.7 True Positive Detection Rate

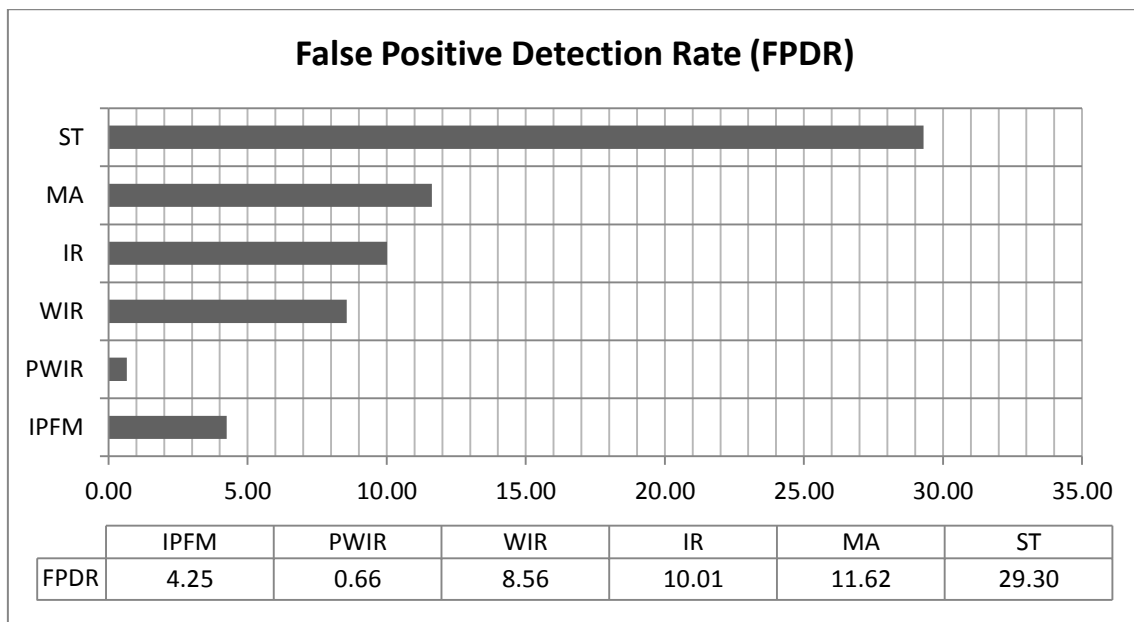


Fig. 6.8 False Positive Detection Rate

Now that we have established the optimal threshold(s) for each algorithm, we can compare the True Positive Detection Rate (TPDR) for each one of them. Figure 6.7 presents the detection rate of the algorithms with respect to the list of annotations provided in the original ECG records we obtained from Physionet. The PWIR algorithm produces the highest detection rate; it has detected 93.80% of the artifacts. The WIR and IPFM are somewhat close seconds with rates of 88.1% and 87.62% respectively. The ST lags behind all other algorithms. Nonetheless, when we take the FPDR into account (shown in Figure 6.8), we notice that that IPFM performs remarkably better than WIR (4.25% to 8.56%). But the PWIR supersedes both with an FPDR of 0.66%. Figure 6.9 shows an example of a signal filtered using both IPFM and PWIR. As it can be seen towards the beginning of the record, the IPFM algorithm incorrectly identifies a string of non-erroneous points as artifacts (the dashed square identifies these samples). Also, the MA exhibits a high FPDR compared to IR and WIR (even though it produced a higher TPDR than IR). Therefore, in order to fairly rank the algorithms by taking into account both the TPDR and FPDR, we have to look at their Performance Index (which we defined as the difference between the TPDR and FPDR). Figure 6.10 shows the Performance Indices for all the algorithms. The PWIR algorithm is the most effective at detecting artifacts with a Performance Index of 93.14%. Also, interestingly, even though both WIR and IR make use of a median based filter, WIR performs notably better than IR. The improvement in performance can only be attributed to the flexibility of the windowed approach when it comes to dealing with HRV signals resulting from highly dynamic heart rates. The IR algorithm examines the whole record at once and therefore, in the presence of rapid heart rate change (a common phenomenon during movement), the median calculated in Equation (6.10) is skewed. Conversely, WIR divides the signal into overlapping windows and thus ensures a more localized calculation of the median. Figure 6.11 displays an example of such phenomenon (the dashed circles identify artifacts).

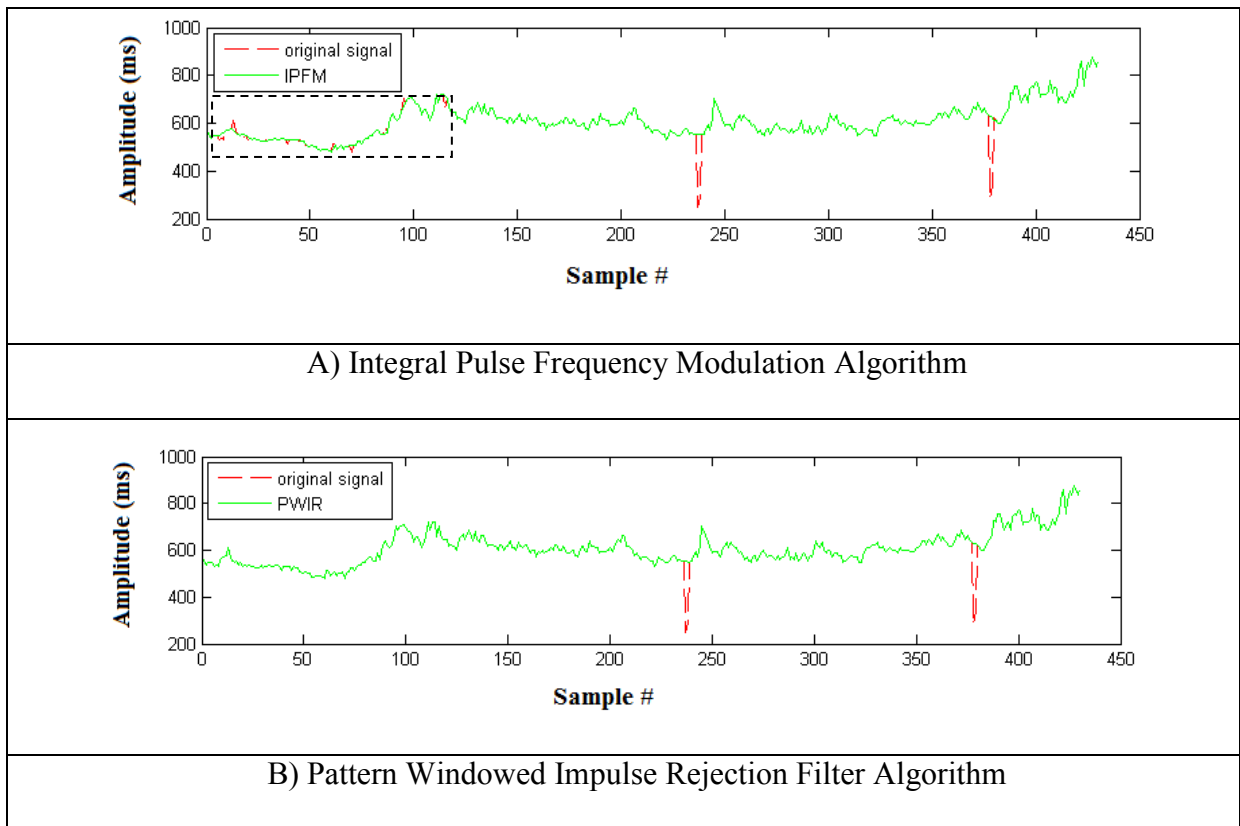


Fig. 6.9 Comparison between the IPFM and PWIR when it comes to FPDR

Figure 6.12 compares the IPFM, PWIR, WIR and IR algorithms more closely by plotting the TRPDR against the FPDR for each algorithm over a threshold range between 0.1 and 15. This shows that the TPDR for the PWIR algorithm increases sharply with respect to FPDR compared to the other algorithms that have slower rising curves. Note that the plot of Figure 6.12 is purposely cropped at FPDR value of 20, as beyond this false detection rate, the algorithms become barely useful.

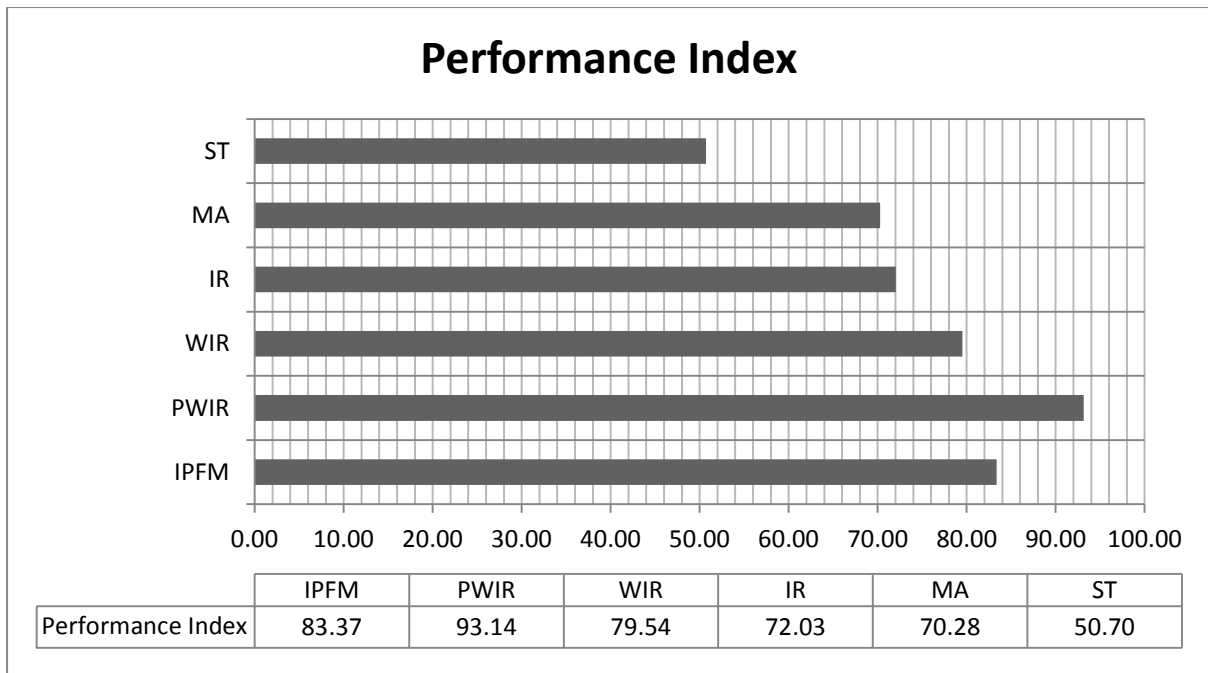


Fig. 6.10 Performance Index for all Detection Algorithms

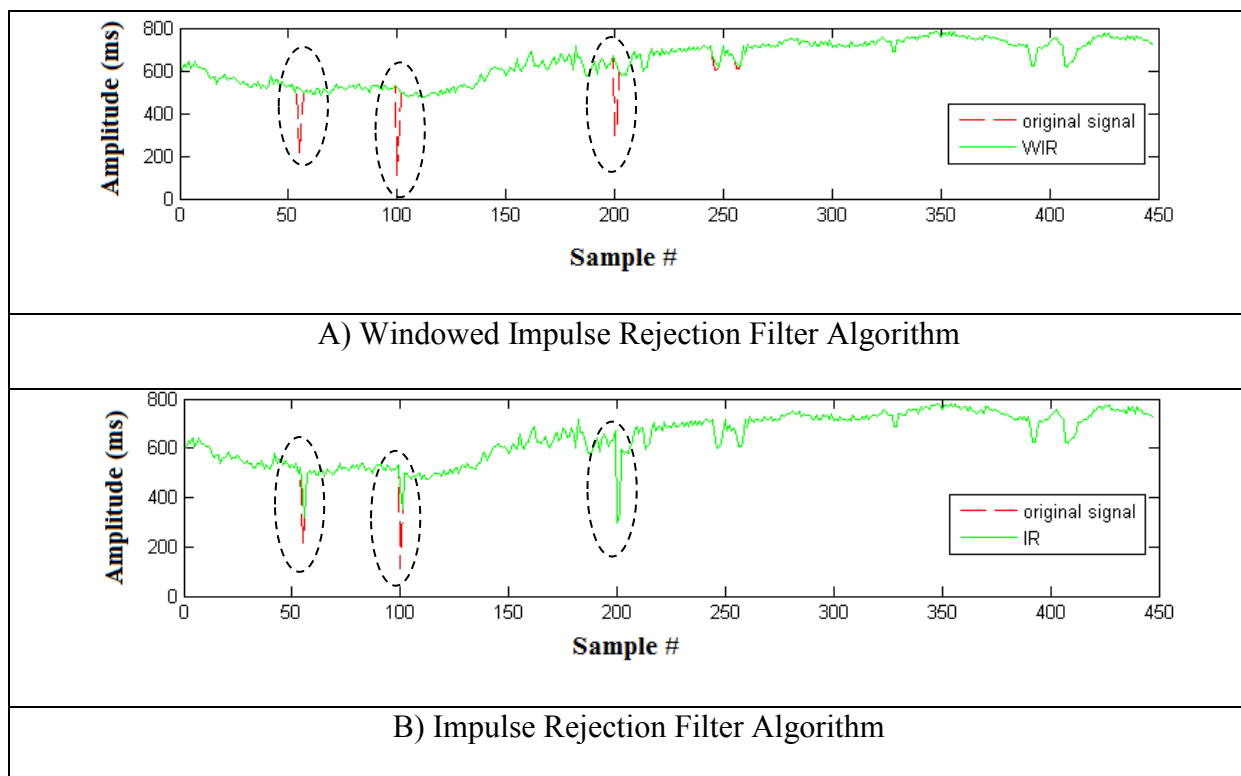


Fig. 6.11 Comparison between the WIR and IR during Quick Heart Rate Changes

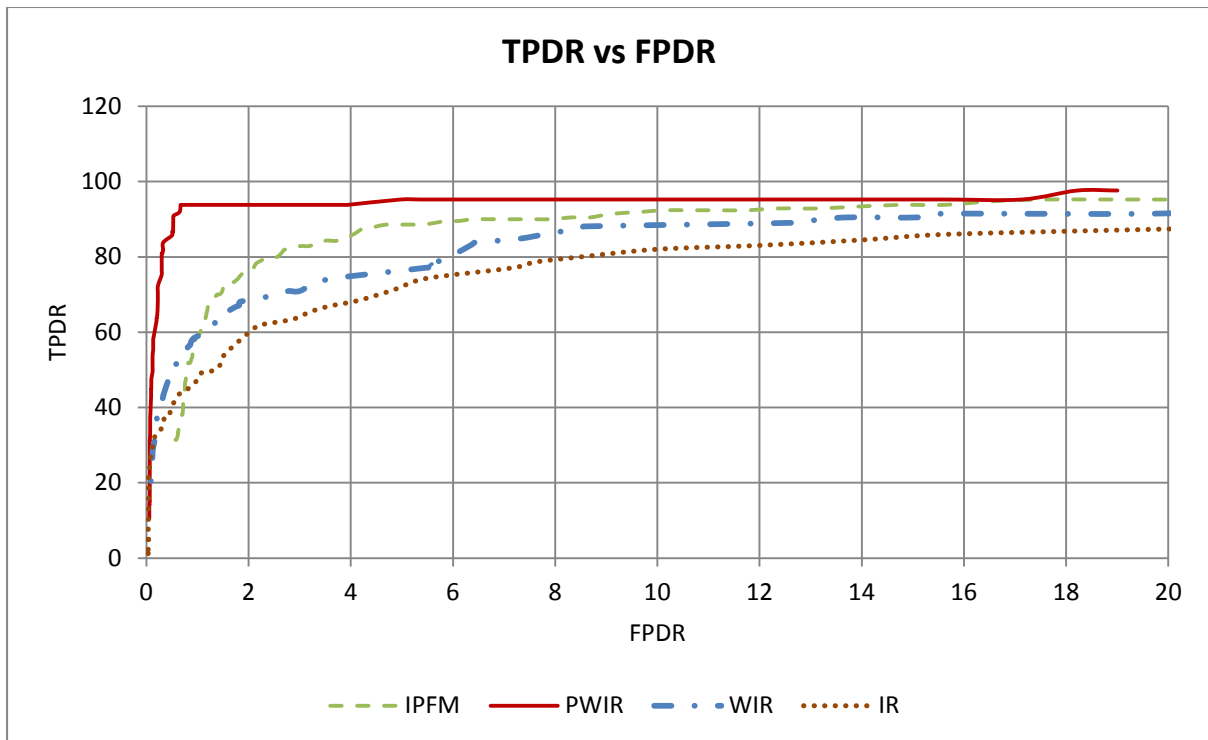
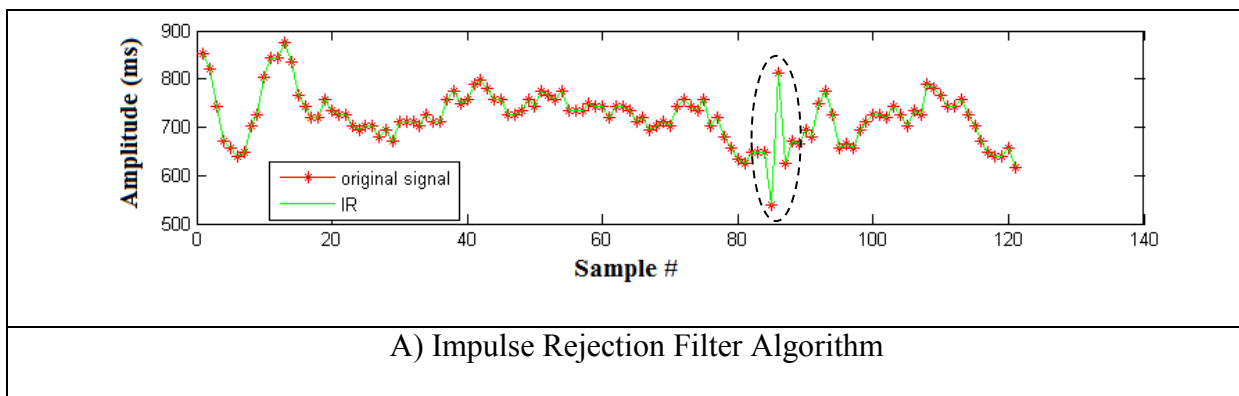


Fig. 6.12 TPDR vs FPDR for the IPFM, PWIR, WIR and IR Algorithms

Both WIR and IR algorithms are very effective at identifying big impulses in an HRV signal that are usually caused by artifacts. Nonetheless, some category 3 artifacts that are caused by ectopic beats tend to display subtle impulses that might be drowned among the other, non-erroneous peaks in the signal (these occur especially in highly variable signals). Figure 6.13 shows an example of such scenario where the IR algorithm fails to detect the artifacts, the WIR algorithm detects one pulse and the PWIR catches both pulses.



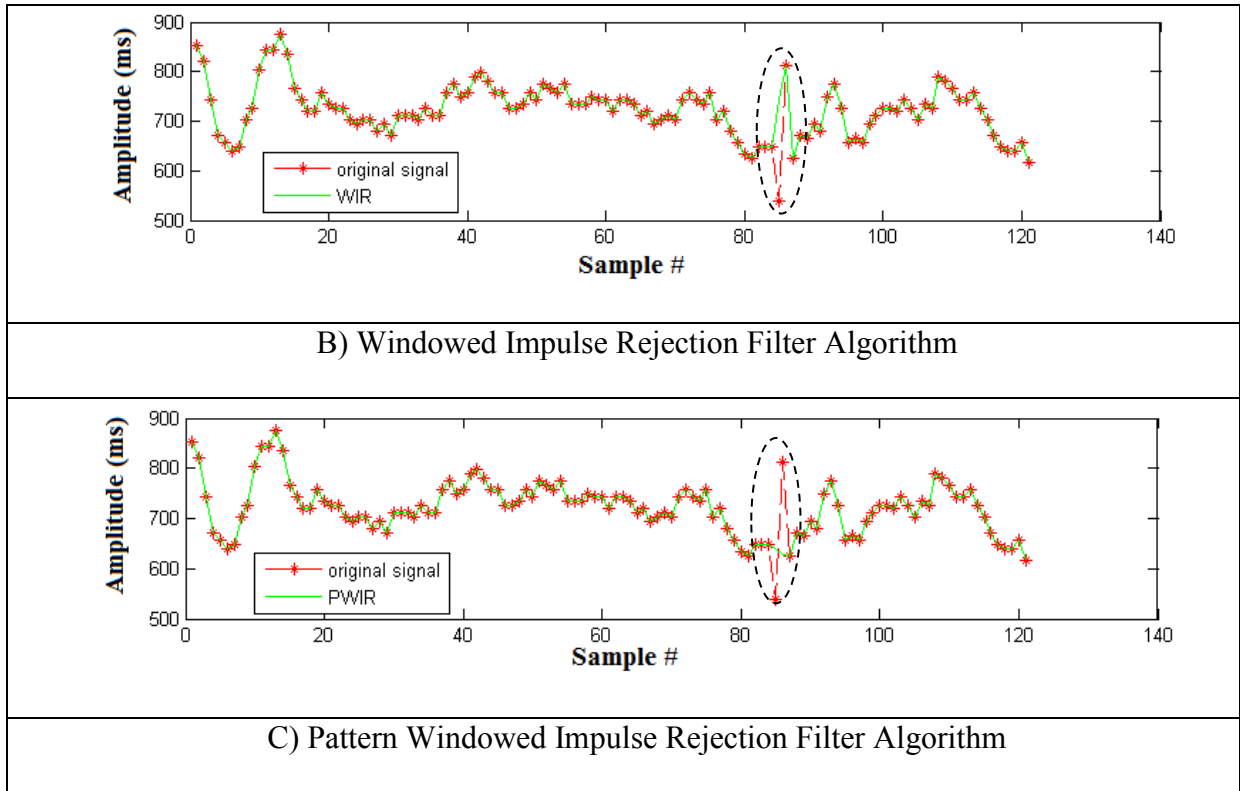


Fig. 6.13 Subtle Category 3 Impulses caused by a Premature Ventricular Contraction

6.7.2 Artifact Correction Evaluation

After detecting the artifacts, the task of minimizing their effect on the integrity of the signal begins. We have proposed the correction procedure presented in Table 6.3. One of the main components of this procedure is the interpolation of new points to replace erroneous ones. We have introduced the Cubic Predictive Interpolation method in this Chapter (Section 6.6.2) as our contribution to this cause. To assess its effectiveness in estimating the best possible points that would fit well within the context of the signal with respect to the other existing techniques, we have devised the following evaluation procedure:

- Randomly choose 123 artifact free ECG records from the Normal Sinus Rhythm Database on Physionet (described in Section 6.7.1.1) and compose their corresponding HRV signals (each source ECG record is 5 minutes long)
- Artificially introduce artifacts using the method used in [80]
- Correct the artifacts using the procedure of Table 6.3

- Compare the original HRV record to the corrected one by calculating the average error for the following time and frequency domain HRV parameters:
 - LF/HF: Low Frequency to High Frequency ratio
 - LF: Low Frequency
 - HF: High Frequency
 - RMSSD: Root Mean Square of Successive Differences
 - Mean R-R: Average R to R interval
 - SDNN: Standard deviation of R to R intervals
- In addition to the aforementioned parameters, calculate the Root Mean Square Error (RMSE) between the original and corrected signals

We ran the correction procedure using the various interpolation algorithms for all the HRV records. We produced an average RMSE and average percentage of error for each HRV parameter discussed above for various percentage of artificially introduced artifacts ((1/12)%, (1/36)% and (1/108)%). The frequency domain parameters were calculated using Welch's method (window size of 256, 50% overlap and 4Hz sampling rate). Table 6.5 summarizes our results. For the smallest percentage of artifacts, the average error for the frequency domain parameters for all algorithms is fairly comparable, with the Cubic, Nonlinear Predictive and Cubic Predictive Interpolation methods slightly edging the other ones. The Cubic Interpolation produces an exceptionally low average error for LF. Reducing the error on the low frequencies is a definite strength of the Cubic Interpolation which produces smooth curves which mimic very well the low frequency sinusoids of the original signal. Nonetheless, using such approach, the high frequency sinusoids of the original signal are not taken into account. In terms of the time domain parameters, the Nonlinear Predictive approach produces a very high average error for RMSSD. The calculation of RMSSD involves adding the difference between successive samples. The difference of successive

samples can differ significantly between the original and interpolated signal, especially at the boundaries of the interpolated sequence (i.e. difference between the sample just before the point of insertion of interpolated sequence and the first interpolated sample and between the last interpolated sample and one following the point of insertion). All other algorithms incorporate in a more effective way the samples surrounding the interpolated area to produce a less erroneous RMSSD. As the percentage of artifact increases, we start to clearly observe the weakness of the Cubic Interpolation in terms of producing large average error on the HF parameter. Also, we start to observe a clear advantage for the proposed method over all other algorithms on the average error for all frequency and time domain parameters being evaluated. Even at the very high artifacts percentage of (1/12)%, the proposed method produces an average error below 3% for all HRV time domain parameters and below 10% for all frequency domain HRV parameters.

Table 6.5 Comparison of Interpolation Techniques

		Linear			Median			Nonlinear Predictive			Cubic			Proposed Method		
		1/12	1/36	1/108	1/12	1/36	1/108	1/12	1/36	1/108	1/12	1/36	1/108	1/12	1/36	1/108
LF/HF	AVG Error %	23.482	7.817	2.350	22.959	8.313	2.516	11.581	6.331	2.427	17.590	6.712	2.133	9.260	5.436	2.186
	SDEV	0.180	0.081	0.024	0.256	0.099	0.027	0.092	0.070	0.025	0.165	0.074	0.021	0.076	0.052	0.022
LF	AVG Error %	5.830	3.273	1.127	6.925	3.878	1.415	8.481	3.752	1.551	5.535	3.161	1.148	5.738	3.130	1.428
	SDEV	0.063	0.041	0.012	0.105	0.052	0.016	0.057	0.036	0.015	0.071	0.042	0.012	0.046	0.031	0.013
HF	AVG Error %	19.094	7.080	2.218	17.096	6.802	2.126	11.111	4.960	1.809	13.266	5.381	1.874	7.757	4.028	1.715
	SDEV	0.077	0.050	0.019	0.092	0.054	0.017	0.073	0.054	0.016	0.073	0.045	0.016	0.074	0.043	0.017
RMSSD	AVG Error %	7.709	2.495	0.702	4.947	1.709	0.561	42.216	9.976	4.450	9.371	2.989	0.844	2.439	1.256	0.542
	SDEV	0.032	0.017	0.005	0.035	0.017	0.005	0.339	0.172	0.112	0.029	0.017	0.006	0.023	0.016	0.006
Mean R-R	AVG Error %	0.078	0.049	0.028	0.131	0.068	0.038	0.098	0.051	0.030	0.079	0.048	0.027	0.100	0.052	0.031
	SDEV	0.001	0.001	0.000	0.001	0.001	0.001	0.001	0.001	0.000	0.001	0.001	0.000	0.001	0.001	0.000
SDNN	AVG Error %	2.155	0.829	0.273	1.771	0.781	0.284	5.481	1.474	0.797	1.741	0.736	0.266	1.475	0.657	0.321
	SDEV	0.021	0.008	0.003	0.018	0.008	0.003	0.079	0.018	0.016	0.018	0.007	0.003	0.013	0.006	0.003
RMSE	AVG	14.376	8.127	4.154	16.511	9.460	4.901	22.955	11.040	5.991	13.524	7.694	3.941	15.569	8.361	4.286
	SDEV	14.916	8.672	4.557	16.690	9.843	5.321	10.963	7.492	5.279	13.472	7.995	4.334	12.283	7.232	3.730

7 Conclusion and Future Works

In this Thesis, we have presented the culmination of our efforts towards the inception of Ubiquitous Biofeedback Multimedia Systems. The aforementioned systems are introduced with the ambition of increasing the level of wellbeing for their users. Also, we presented a Ubiquitous Biofeedback reference model that standardizes the various modules and components involved in U-Biofeedback systems. The reference model defines two processes, the awareness process and the assistive process. The first is in charge of informing users of their physiological parameters. The second is responsible for helping them fine tune these parameters in the goal of leading a healthier life.

The following Sections discuss the accomplishments of this Thesis and the possible directions of future works.

7.1 Accomplishments

In addition to formalizing the concept of U-Biofeedback and introducing its corresponding reference model, we have contributed several methods and algorithms that make the realization of complying systems possible. In particular, our contributions focus on U-Biofeedback stress management systems and are summarized in the following Sections. Also, we have implemented two of such systems, and incorporated the aforementioned methods and algorithms in their design.

7.1.1 Acute Stress Detection Algorithm

We devised an algorithm to detect acute mental stress events on individuals being monitored by a U-Biofeedback system. The algorithm compares the measured physiological information to a benchmark in order draw conclusions regarding the stress conditions. In our

long term evaluation that involved 3 subjects over a period of 17 days, we found that the algorithm, on average for all subjects, correctly identified acute stress episodes 89.63% of the times with an average false detection rate of 5.55%.

7.1.2 Stress Accumulation Algorithm

In addition to detecting acute stress periods, it is also important to keep track of stress accumulations. This is essential since we do not always experience stress as distinct severe episodes, but also as slow accumulations that result in adverse short term and long term effects on our wellbeing. We have devised a method to model short term and long term accumulations of stress. The method was incorporated into a Biofeedback Serious Game (BSG) and the resulting stress accumulation signal was used to control its gaming scenario.

7.1.3 Personalized Relaxation Mathematical Model

We introduced a mathematical model to personalize the relaxation process. The goal of the personalization is to recommend to users, after a stress event, the optimal relaxation technique (the one with the highest chance of succeeding in diffusing the stress situation). In order to achieve that, the model takes into account the preferences of the user, the performance of relaxation techniques that have been already consumed and a correlation factor between the various techniques (since several techniques share numerous similarities and therefore, if one of them works, it is highly probable that similar ones will, and vice versa). We evaluated the mathematical model, using a U-Biofeedback system, with 2 subjects over a period of 47 days. We found that personalization on average increased the time subjects spent consuming relaxation techniques by 23.69% (compared to when the personalization was not applied). This caused their level of relaxation to increase as it was evidenced from the reduced Stress Index.

7.1.4 HRV Artifact Detection

We made use of Heart Rate Variability (HRV) information to evaluate mental stress levels of individuals. These signals are occasionally plagued by artifacts. Therefore, we devised the Pattern Windowed Impulse Rejection (PWIR) artifact detection algorithm. The algorithm exhibited a favourable performance with respect to existing ones with a true detection rate of 93.80% and a false artifact detection rate of 0.66% (compared to the IPFM's true detection rate of 87.62% and false detection rate of 4.25%).

7.1.5 HRV Interpolation Algorithm

After detecting the artifacts, we corrected these erroneous samples using insertion, deletion and interpolation operations. In particular, the interpolation operation tends to be challenging as it can introduce unwanted features to the HRV signal. We proposed a method called Cubic Nonlinear Prediction to implement the interpolation operation. In order to evaluate the effectiveness of this method, we artificially introduced artifacts to otherwise artifact-free HRV records to assess the effect of interpolation on the integrity of the signal. We found the proposed method to out-perform the existing ones in terms of minimizing the error on the HRV time and frequency domain parameters. In fact, even at the very high artifacts percentage of 8.33%, the proposed method produces an average error below 3% for all HRV time domain parameters and below 10% for all frequency domain HRV parameters.

7.1.6 U-Biofeedback Systems

We have implemented two U-Biofeedback systems that faithfully follow the U-Biofeedback Reference model. The first one is called Office Stress Check (OSC) and is designed to monitor the stress level of office employees and inform them of acute stress events. Also, the OSC application is accompanied by a Relaxation Assistant that assists the user in the relaxation. The second one is called Botanical Nerves and is an example of what

we call Biofeedback Serious Games. The application incorporates gaming components in order to inject an element of entertainment into biofeedback process. It also accompanied by a relaxation assistant.

7.2 Future Works

We will divide the future works into two categories, improvements over existing work and possible future directions.

7.2.1 Improvements over Existing Work

Many improvements can be made to the two developed U-Biofeedback systems. The following is a non-exhaustive short-list of possible improvements:

- Improve history monitoring by incorporating visual features that highlight short and long term trends in the data for the OSC application
- Add multi-player gaming capabilities to the Botanical Nerves game and assess the impact of such approach on the dynamics of stress and relaxation
- Introduce a feature to connect the Botanical Nerves game to social media websites

Also, in terms of stress assessment, it might be useful to incorporate other sensors that measure physiological parameters that are reflective of mental stress. This can potentially improve stress detection and quantization accuracy. Moreover, investigating the use of a camera to collect the necessary physiological signals to measure stress would eliminate the need for the user to wear a sensor(s) in order to use the system.

7.2.2 Possible Future Directions

We envision a future where sensors are minimized in size, incorporated into clothing, or replaced by contactless ones (optical sensors). Therefore, continuous monitoring and assessment of internal physiological processes will definitely be a common practice for many

purposes such as health monitoring, active biometrics Ubiquitous Biofeedback and gaming, among others.

Nonetheless, as the size of the data increases, the difficulty in finding relevant information and recording patterns becomes more challenging. Therefore, data mining techniques might be required for that purpose. Also, with multiple sources of information coming from numerous sensors, effective data fusion techniques are necessary in order to draw a common conclusion from the various signals. Furthermore, security and confidentiality will become a prominent and pressing issue and therefore should be studied meticulously. These signals reveal very intimate details about us, and therefore, must be handled prudently.

In terms of mental stress assessment, algorithms designed for that purpose can be used to personalize computing experiences, such as the way a mobile phone assistant responds to queries by being more compassionate when elevated stress is detected. Or the way a computer program re-arranges calendar items in order to push back on stress inducing tasks when the user is already experiencing stress. Numerous other scenarios can be dreamed in this context and the possibilities are endless.

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