KOPOS: A FRAMEWORK TO STUDY AND DETECT PHYSICAL AND COGNITIVE FATIGUE CONCURRENTLY

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KOPOS: A FRAMEWORK TO STUDY AND DETECT PHYSICAL AND COGNITIVE FATIGUE CONCURRENTLY

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To my family and friends.

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ABSTRACT

KOPOS: A FRAMEWORK TO STUDY AND DETECT PHYSICAL AND COGNITIVE FATIGUE CONCURRENTLY

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Fatigue is one of the most prevalent phenomena in human beings, and yet its detection is highly subjective and poorly understood. The phenomenon of fatigue has a huge impact on performance, the ability to execute tasks safely and correctly, and the ability to retain or secure a job. Fatigue can be classified into two types: physical and cognitive fatigue. Physical fatigue may occur due to excessive physical exertion, while cognitive fatigue may occur due to excessive mental exertion. Historically, these two types of fatigue have been studied independently. However, in the real world, although these often occur at the same time, it has not always been easy to distinguish them or to understand which type of fatigue impacts the other. Therefore, it is important to study them together rather than separately in order to enable effective intervention and rehabilitation, regardless of the type of fatigue.

This thesis presents a system designed to aid in human-centered studies that focus on the intervention of fatigue. It proposes a system that can detect both types of fatigue using the same setup. The system monitors the state of the body using physiological wearable sensors, which help us analyze the changes in the body due to fatigue. Using this multisensory approach, the system detects both physical and cognitive fatigue while collecting contextual data that help understand and predict occurrences of fatigue.

The sensors employed vary: some are specific for detecting cognitive fatigue, while some are specific for detecting physical fatigue. Others can be used to detect both types. This creates a computational challenge in terms of sensor fusion and data processing. To address this, the system uses a Dynamic Data Driven Application System (DDDAS) paradigm and context-aware fusion techniques. These techniques allow the system to handle the different combinations of sensors and detect fatigue with higher accuracy.

The main contributions of this thesis can be summarized in the following four points.

- It proposes a framework to detect and help study and analyze the two types of fatigue.
- The proposed system addresses the sensor fusion challenges associated with different combinations of sensors for each type of fatigue.
- The system takes into account the human behavior/activity context in which the data is collected.
- The proposed system was evaluated using data from a user study that was conducted.

CHAPTER 1
INTRODUCTION

1.1 Background

A plethora of diseases and disorders affect human beings. These may range from common and rarely lethal cases such as rhinovirus to uncommon and deadly diseases such as Huntington's Disease. Some of these diseases can be cured while others cannot. These diseases can affect multiple systems in the body and often induce symptoms indicating their effect. For example, cardiovascular diseases can show symptoms like high blood pressure and an irregular heart rate [1]. One of the most common symptoms of several diseases is fatigue [2]. The symptom of fatigue can exacerbate any such condition and slow down recovery. Therefore, it is important to monitor these symptoms in conjunction with fatigue in order to check the progression of the disease as well as to check the effectiveness of the cure.

The advent of sensor technologies has provided us with better tools to monitor and control systems. Sensors allow us to monitor systems as complex as the human body. Multiple sensors with different sensing technologies have been created to monitor different aspects of the human body. For example, a sphygmomanometer is used to monitor blood pressure.

Using multiple sensors, known as multi-sensing or multi-modal sensing, can provide information about multiple aspects of a human body and allow for a more holistic approach in human health monitoring. This type of sensing can lead to a more accurate and comprehensive representation of the human state. It can also provide important redundancies in human health monitoring. For example, in cardiovascular diseases, multi-sensors enable monitoring of heart rate, blood flow, and blood pressure [1].

This thesis focuses on one of the most common symptoms of multiple diseases, fatigue.

1.2 Fatigue

Fatigue is a common phenomenon that affects humans and is highly subjective and poorly understood phenomenon. The study of fatigue can be found in multiple areas and scientific fields, and therefore, its definition is in contention. Jensen and Given [3] defines fatigue as

> *"Acute fatigue is most often caused by excessive physical or mental exertion and can be relieved by rest. Normative fatigue may be influenced by circadian rhythm and results from the activities of daily living, while chronic fatigue is most often prolonged by stress or tension on the body and is less likely to be relieved by rest alone."*

Fatigue may present itself as a symptom of a disease or as a result of everyday activities. Some of the diseases in which fatigue is a symptom of include, Multiple Sclerosis (MS), Traumatic brain injury (TBI), and Parkinson's Disease (PD), among others [4, 5, 2]. Monitoring fatigue as a disease symptom allows us to monitor the progression of the disease and the effectiveness of the treatment administered. It can also indicate other aspects regarding the patient's health, such as depression and quality of life [6]. Apart from medical applications, monitoring fatigue is also important for daily life. Workers or air traffic controllers who must always pay attention to various things may get tired, leading to catastrophic situations.

Fatigue can be categorized into physical and cognitive fatigue. Physical fatigue can occur due to excessive physical activity. This type of fatigue may be localized to a muscle group or cause an overall sense of fatigue [7, 8]. Cognitive fatigue, on the other hand, can occur due to excessive mental activity. It may result in a loss of cognitive control, causing high-level information processing and reduced attention [9].

In the real world, the activities that induce fatigue may not be easily separable. The actions that may lead to the two types of fatigue may be the same or different. Some activities demand both physical and cognitive efforts, for example, maintenance workers in factories require to work and perform physical labor for repairs, but at the same time, they need cognitive capabilities to troubleshoot the problems that arise. These types of activities may induce both physical and cognitive fatigue.

1.3 Motivation

Traditionally, the two types of fatigue have been studied separately. Researchers have approached this topic in different ways. Some researchers have studied fatigue by analyzing the subjective experience of the participants. This is the most common way of studying fatigue. Typically, the subjects are asked to fill out a survey rating their subjective feelings. Some common ways of measuring subjective fatigue are the Chalder Fatigue Scale (CFS) [10], Krupp's Fatigue Severity Scale (FSS) [11], the Modified Fatigue Impact Scale (MFIS) [12], and the Visual Analogue Scale (VAS) [13]. Although these methods have been proven to be effective in quantifying fatigue, they are susceptible to human bias. For example, in the aviation industry, pilots use the IMSAFE (Illness, Medication, Stress, Alcohol, Fatigue, Eating) [14] checklist to determine if they are fit to fly. It was found that 70-80 % of pilots inaccurately assessed or misrepresented their fatigue [15]. Therefore, relying solely on a subjective measure to determine fatigue in such a scenario may raise a safety concern. Objective measures like physiological parameters have also been studied. Signals like electrocardiogram (ECG), electroencephalogram (EEG) [16], and electromyogram (EMG) [17], among others have been used commonly to study fatigue.

In recent years, studies have tried to leverage wearables to assess fatigue during Activities of Daily Living (ADL). A study by Aryal et al. [18] used wearable sensors to assess fatigue in construction workers. They utilized heart rate, skin temperature, and EEG signals to monitor physical fatigue. Another study by Maman et al. [19] focused on detecting physical fatigue using wearable sensors. The authors measured the heart rate and body posture during different physical tasks to monitor fatigue.

Measuring and monitoring fatigue is a relatively hard task as it affects multiple systems of the body. As stated in section 1.2, two main types of fatigue are traditionally studied individually, although both occur in the real world at the same time. Studying them individually obscures information that may be useful in determining how the fatigue is induced during the patient's everyday life. Therefore, studying these two simultaneously provides a more accurate representation of the real world and gives a broader view of the effect of fatigue and affords us the opportunity to study the context in which the fatigue occurs. For example, if the fatigue occurred during a purely physical task or during a mix of a physical and cognitive task. When the two types of fatigue occur at the same time, they may interact with each other. Studying this interaction may help us understand the effect of the mechanism and the effect of fatigue on the body. When studied individually, we may miss this interaction. Therefore, it is prudent to study them together.

Some researchers have tried to study the two types of fatigue together. A study by Marcora *et al.* [20] found that mental fatigue affects exercise tolerance. Another study by Xu *et al.* [21] found that physical activities affect mental fatigue. They found that physical activities increased mental fatigue. A study was done by Paul *et al.* [22] on people suffering from multiple sclerosis (MS) looked at physical and cognitive fatigue. They found that, although the subjective evaluation of physical and cognitive fatigue increased, their objective performance showed no statistical change. This indicates that a better objective measure is needed to assess and identify fatigue.

1.4 Proposed Solution

This thesis develops a novel fatigue detection and tracking system that relies on context-aware multi-sensor data fusion to track fatigue occurrences during different ADL. The proposed system can be used as a diagnostic and monitoring tool for fatigue and assess its impact on diseases or disorders. The system can also be used for enabling effective rehabilitation therapy: it allows us to account for performance decline and determine when intervention is needed. The proposed system can also be used as a research tool to study both types of fatigue under simulated real-life conditions and their relationship with each other.

1.5 Novelty

The main novelty of this work can be summarized in the following points.

- The framework proposed detects and helps study the two types of fatigue.
- The system handles the sensor fusion challenges associated with different combinations of sensors for each type of fatigue.
- The system also takes into account the context in which the data is collected.
- The proposed system was evaluated using data from a user study that was conducted.

1.6 Research Questions

To evaluate the design and the usability of the design, three research questions will be asked:

Q1: Can we use physiological sensors to create a multi-sensory system to detect, study, and account for fatigue? Can we use such a system for medical applications?

Q2: Can we make different models to detect the two types of fatigue? If so, can we combine the two models into a unified system that detects both types of fatigue?

Q3: What are the challenges associated with creating the above system? How will we handle the challenges? Can we use the collected contextual information (e.g. type of task performed) to get better accuracy?

1.7 Thesis Structure

This section lists the structure of this thesis.

- Chapter 2 discusses the importance of physiological sensors and lists some applications of them.
- Chapter 3 discusses previous systems designed to detecting physical fatigue and accounting for it during rehabilitation tasks.
- Chapter 4 reviews systems designed to combine physical and cognitive fatigue in a single framework. It also discusses the lessons learned from creating such systems.
- Chapter 5 discusses the proposed system named KOPOS.
- Chapter 6 discusses the studies performed.
- Chapter 7 discusses the analysis performed on the collected data.
- Finally, Chapter 8 provides the concluding remarks.

CHAPTER 2

PHYSIOLOGICAL SENSING AND APPLICATIONS

This chapter describes the usefulness of physiological sensing. It also lists and describes some common sensors used to monitor physiological activities. Finally, the chapter lists some studies performed to monitor and detect physiological conditions. The studies monitor conditions that are associated with fatigue.

2.1 Introduction

Sensing the state of the body opens the door to numerous applications and allows us to monitor the effects of a stimulus on the body, e.g. fatigue. It also allows us to diagnose a patient by comparing their current condition with the disease state. Physiological sensing enables us to detect severe conditions like cardiac arrest or an epileptic attack.

Often, physiological sensors can be easily integrated into a digital system. These sensors record various aspects of the body (such as brain activity) and digitize them. This digital signal can be transmitted to a computer or any other smart device and can be reconverted back to its original signal to view and analyze it. Unlike the previously mentioned sensors, some sensors do not convert the data into its digital form. An example of this would be a stethoscope. Integrating these analog sensors is a challenging task. Luckily, a digital form of most of these sensors has been created. An alternative digital tool of a stethoscope is a microphone that can be attached to the chest to record the sounds.

A common way of integrating physiological sensors in an application is depicted in the pipeline shown in Figure 2.1. The very first step in integrating these sensors is the actual sensing part. For this, we need first to determine what we are sensing. For example, if we are sensing the function of the heart, we can look at its electrical activity or look at blood pressure.

After selecting the sensor, we can record the digital signal. These digital signals are sampled from real analog signals and contain a lot of noise and distortions. In signal processing, noise can be defined as any component of the signal that is unwanted [23]. For example, if a signal contains high-frequency elements that are not relevant, they can be classified as noise. There are multiple ways that noise can be present in a signal. Motion artifact is one of the most common noises in a signal. This noise can occur due to the motion. Power line noise/line noise/electric hum is another type of noise that is quite common. This noise occurs due to the alternating current of the power mains. In the United States, this noise has a frequency of 60Hz. Noise obscures the signal and hinders the application. The signal must be processed to revert it as close to the original signal as possible. There are multiple methods to reduce noise. One of the most common ways is signal filtering.

After the filtered signal is extracted, it will help us understand the state of the body. To achieve this, features from the signal must be extracted. These features quantify and identify the signal. These features are then used to analyze the state of the body.

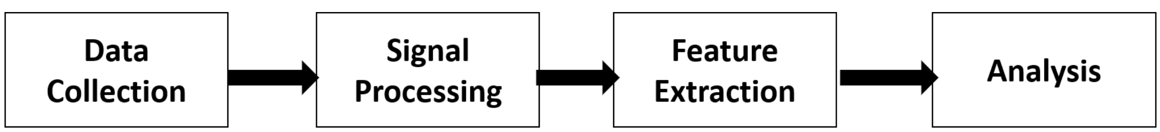


Figure 2.1: Sensor Integration Pipeline. A common way in which sensor-based systems are designed. This is the pipeline that is followed in the sensory systems presented in this thesis.

2.2 Biosensors

Many sensors have been developed to record various physiological aspects of the human body. This section explains how some common sensors work. The sensors described in this section monitor the physiological systems that are associated with fatigue.

2.2.1 Electrocardiogram (ECG)

The human heart is a muscular organ that pumps blood to the different parts of the body. The heart contains four chambers, two atria, and two ventricles (Figure 2.2) [24]. The atrium collects the blood coming into the heart while the ventricles push blood out of the heart. To achieve this, the four chambers can contract and expand. After collecting blood, the atria contract, forcing blood into the ventricles. The ventricles contract and expel blood from the heart.

The heart contains an electrical pathway, which controls muscle contraction and relaxation in the heart's chamber [24]. The heartbeat has a fixed sequence. First, the two atria contract and force blood into the ventricles. Then the ventricles contract and expel blood from the heart. When the ventricles contract, the atrium expands, allowing it to collect blood into the heart. On the other hand, when the atrium contracts, the ventricles expand, allowing it to receive the blood. This forms a rhythm, also known as a sinus rhythm.

ECG is a sensor to measure the electrical activity of the heart. It provides a graph of the voltage over time. The ECG graph is divided into three parts (Figure 2.4). The first part of the ECG signal is the P wave, representing the atria's depolarization. The next is the QRS complex, which represents the depolarization of the ventricles. The last part is the T wave, which represents the repolarization of the ventricles [24].

The most common way of recording ECG is using the Einthoven's triangle [25]. This method dictates the position on the body where surface electrodes should be attached to record the ECG signal. Figure 2.3 illustrates Einthoven's triangle. Three locations are described by the triangle, Right Arm (RA), Left Arm (LA), and Left Leg (LL). This setup is grounded using a fourth electrode attached to the right leg. Most commonly, the RA electrode is attached to the right wrist, the LA is attached to the left wrist, and the LL is attached to the left ankle. ECG is recorded using a combination of any two of these three electrodes. This means that three combinations can be used to record the ECG signal. These combinations are called Lead I, Lead II, and Lead III. Lead I is recorded between

RA and LA, Lead II between RA and LL, and Lead III between LA and LL [24].

The ECG helps to monitor the body's cardiovascular system. This is a vital system and needs to be monitored when investigating fatigue. Studies have shown that fatigue affects the body's cardiovascular response [26, 27]. Therefore, monitoring the system helps to identify fatigue and investigate symptoms of fatigue.

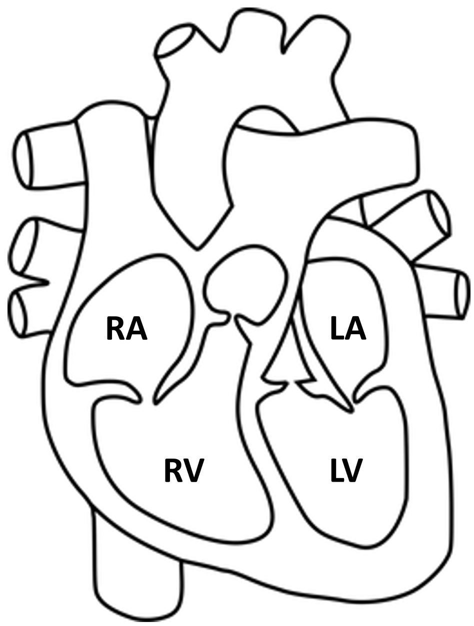


Figure 2.2: Chambers of the heart. Right Atrium (RA), Left Atrium (LA), Right Ventricle (RV), and Left Ventricle (LV) [28]. The atria collect blood coming into the heart. The ventricles push blood out of the heart.

2.2.2 Electromyogram (EMG)

Muscles constitute a large portion of the human body. There are three types of muscle cells, smooth muscles, cardiac muscle, and skeletal muscle [24]. Smooth muscles are found in the walls of the internal organs. Cardiac muscles are found in the walls of the heart. Skeletal muscles are attached to the bones by a tendon and provide support and structure to the human body. These muscles also aid in movement. Amongst the three, these muscles are under voluntary control.

The muscles or muscular tissue consists of muscle cells bundle up together. This tissue

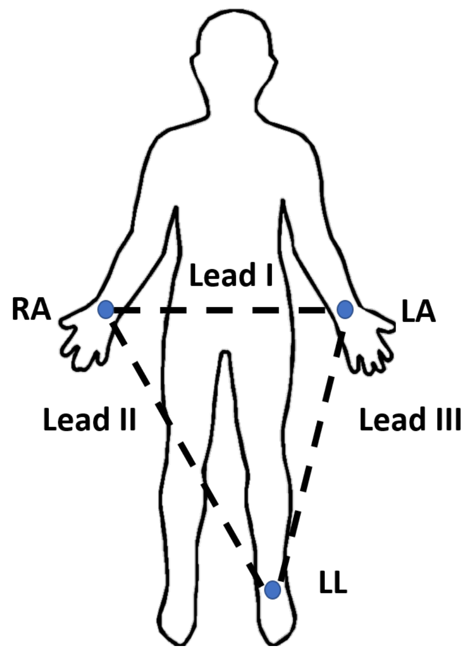


Figure 2.3: Einthoven's Triangle: Right Arm (RA), Left Arm (LA), and Left Leg (LL). This electrode configuration is followed to collect ECG signals.

interfaces with the motor neuron at the neuromuscular junction [24]. Through this junction, the brain can control the contraction and relaxation of the muscle.

In EMG, this contraction is recorded as the change in voltage between two electrodes. These two electrodes must be placed at either end on the longitudinal midline of the muscle. When the muscle is activated, the voltage across the muscle is picked up by these electrodes. EMG provides a graph of voltage over time. Figure 2.5 illustrates the EMG signal.

Fatigue, especially physical fatigue, has been shown to affect muscle activity. Studies have shown that fatigue can lead to reduced muscle activation [29]; in addition, studies have also shown that due to fatigue, the median frequency of EMG signals will decrease [30, 31, 32]. These factors indicate the usefulness of monitoring muscle activity during fatigue.

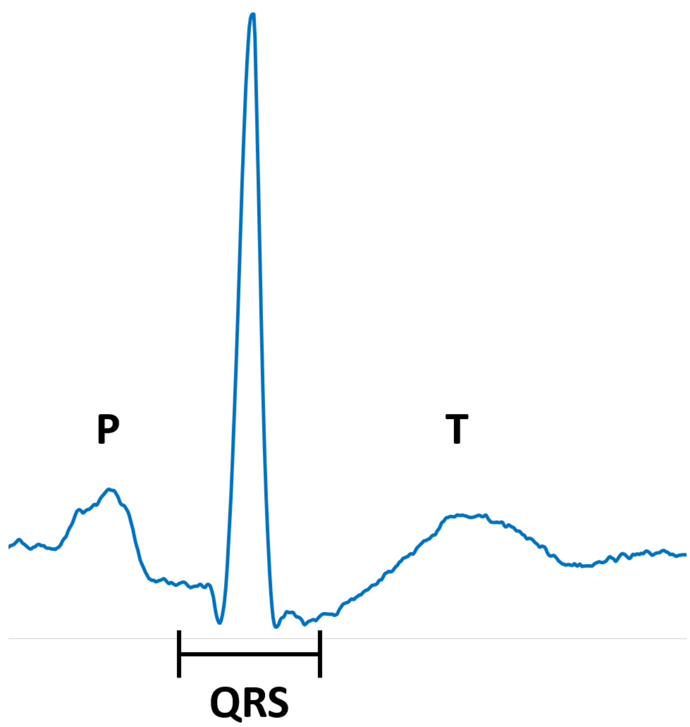


Figure 2.4: ECG Waveform. P wave, QRS complex, and T wave. This waveform is repeated throughout the ECG signal. Analysis of this waveform helps us study the physiological changes in the heart.

2.2.3 Electroencephalogram (EEG)

The human brain is one of the most important parts of the body. It controls the different body systems as well as performs cognition. The brain is made up of multiple cells including neurons that are connected in a network-like fashion. The site of connection between two neurons is called the synapse. The two neurons communicate with each other using chemicals known as the neurotransmitter.

In EEG, this communication is picked up using surface electrodes. The brain activity is recorded as the voltage of the electrical impulses over time. The brain is divided into the following three main parts, the cerebrum, the cerebellum, and the brain stem [24]. The function of the brain is allocated between these parts. The cerebrum is further divided into four lobes, frontal lobe, parietal lobe, temporal lobe, and occipital lobe [24]. Figure 2.6 illustrates the different parts of the brain. These lobes handle different functions of

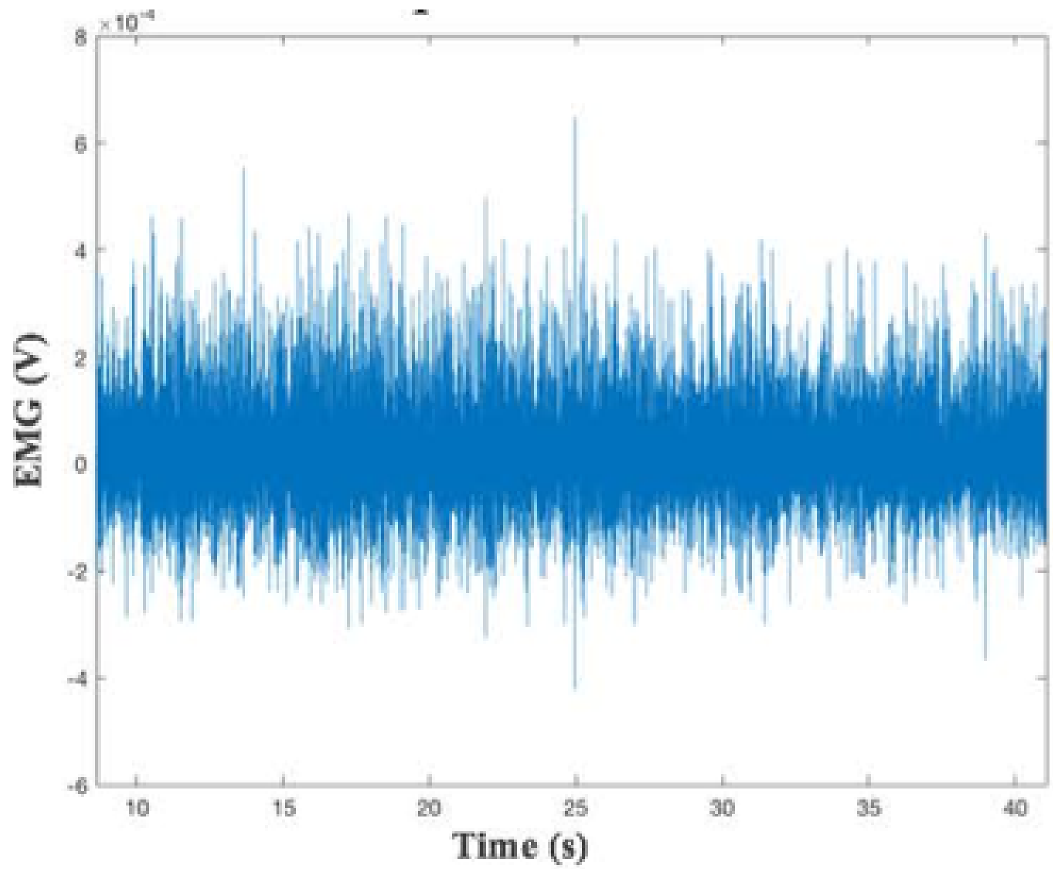


Figure 2.5: EMG Signal. This is a sample segment of the EMG signal. The signal represents the electric potential across a muscle. If the muscle is activated, the amplitude of the signal increases. Analysis of this signal helps us study the physiological changes in the muscle.

the cerebrum. Among other things, the frontal lobe is responsible for executive function. The parietal lobe is responsible for sensory processing. One of the things the temporal lobe is responsible for is auditory processing. The occipital lobe is responsible for visual processing.

To measure brain activity, EEG is recorded from multiple positions on the scalp so that data from the different parts of the brain can be recorded. Recording the EEG of different parts of the brain is very important because many tasks performed by the brain may require different processes. For example, understanding your environment may require visual, sensory, and auditory processing and executive functions. As mentioned earlier, they are processed by different parts of the brain.

To do this, two sensor configurations can be used, the 10-20 and the 10-10 configuration. These configurations dictate the positions where the sensors must be placed to record the EEG signal. Figure 2.7 illustrates the two configurations.

Fatigue, especially cognitive fatigue, can affect brain activity. Studies have shown that changes occur in the brain's frontal, central, and posterior areas due to fatigue [33]. In addition, studies have shown that cognitive fatigue affects a part of the brain called caudate [34]. Therefore, it is essential to monitor brain activity while studying fatigue.

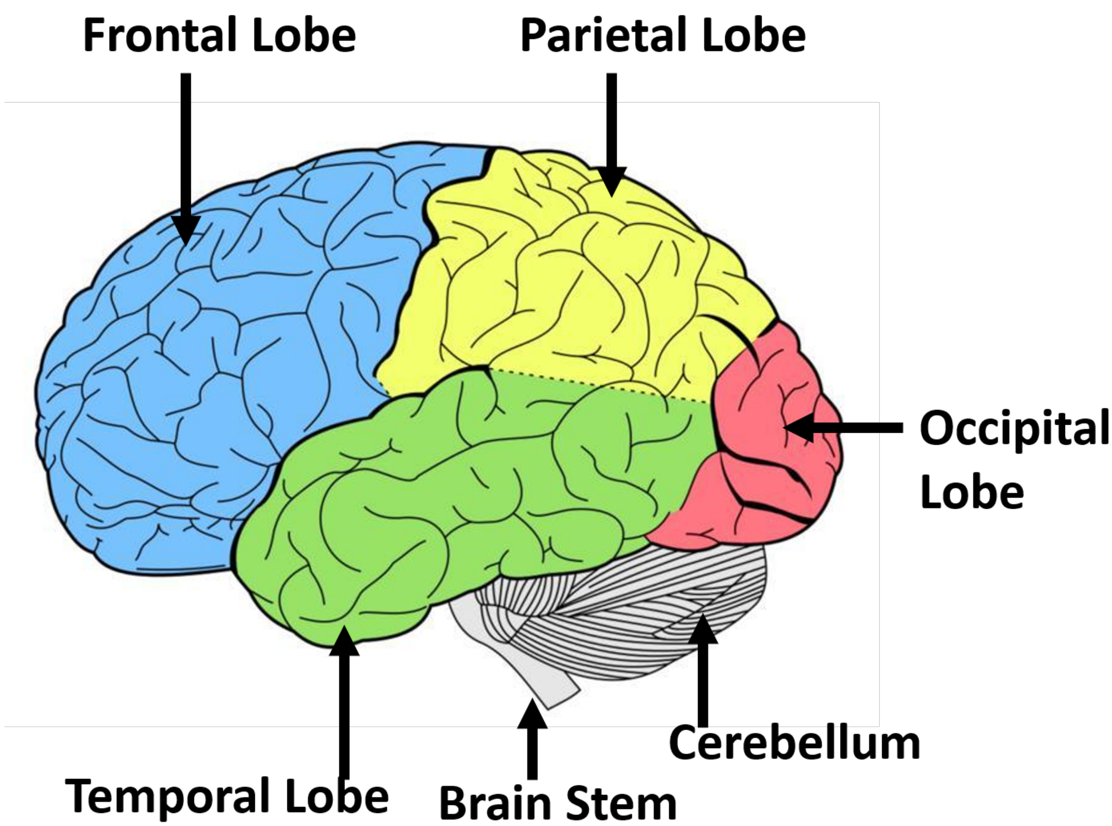
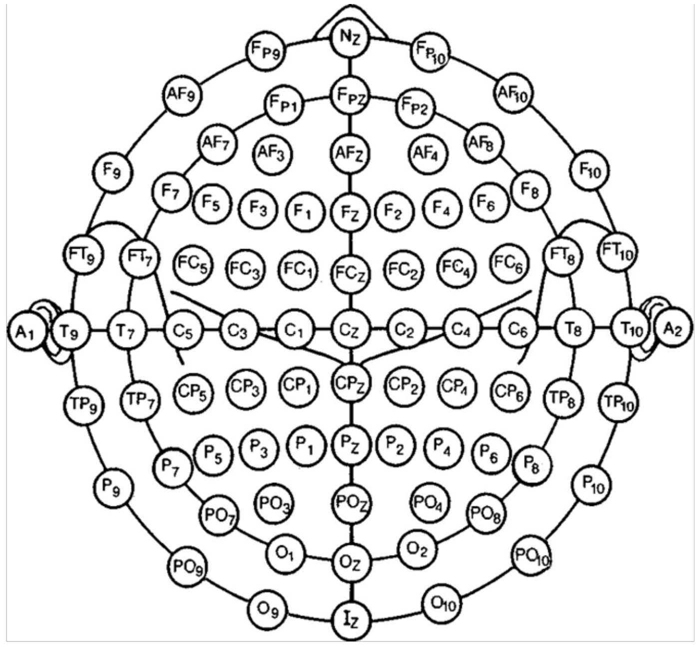
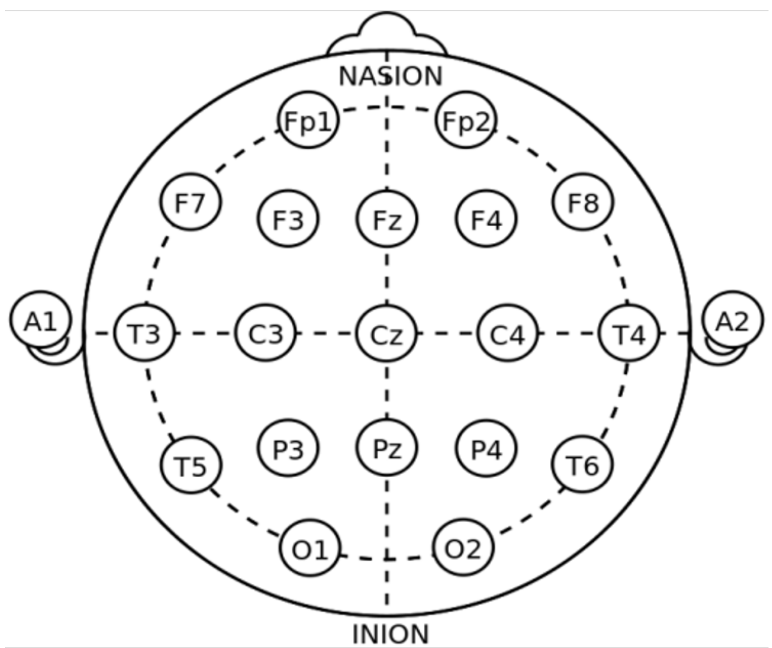


Figure 2.6: Parts of the brain [35]. The figure shows the different parts of the brain. The functioning of the brain is divided into these parts. The frontal lobe handles executive functioning, the parietal lobe handles sensory information, the temporal lobe handles auditory information, and the occipital lobe handles visual information.



(A)



(B)

Figure 2.7: EEG electrode positions (A) 10-10 Electrode System [36] (B) 10-20 Electrode System [37]. These are standard configurations from which the EEG signals are extracted. These positions allow us to monitor the different parts of the brain.

2.2.4 Oximeter

In the human body, the blood carries oxygen to different parts of the body. It travels all across the body through the circulatory system. It collects the oxygen from the inhaled air in the lungs and transmits it throughout the body. Blood contains a specialized cell known as the Red Blood Cells (RBC) [24]. RBCs contain a protein known as hemoglobin. This protein binds with oxygen in the lungs allowing the lungs to transmit the oxygen. As the blood travels through the body, this oxygen is transferred to the body's different cells. When the oxygen is bonded with hemoglobin, it is known as oxyhemoglobin. Hemoglobin without oxygen is known as deoxyhemoglobin.

An oximeter is a sensor that measures the oxygen level in the blood. It measures oxygen as the percentage of oxygen in the blood. More specifically, it gives peripheral oxygen saturation (SpO_2). An oximeter works on the principle of the absorption of light by a medium. It transmits light through a thin part of the body, most commonly fingertip. Using this it measures the amount of oxyhemoglobin and deoxyhemoglobin in the blood using the Beer-Lambert law [38]. This law expresses the absorbance of a medium through the equation $A = \varepsilon lc$. Here A represents the absorbance, ε represents the absorptivity, l represents the optical path length, and c is the concentration. It then calculates the percentage of oxygen in the blood.

2.2.5 Electrodermal Activity (EDA)

In the human body, neurons carry information from the brain and spinal cord to different parts of the body. One of the nervous system subdivisions is the Sympathetic Nervous System (SNS) [24]. SNS controls the homeostasis of the body. In biology, homeostasis refers to the ability to maintain the state of the body. It also controls the fight or flight response of the body.

There is a close link between psychological arousal and the SNS. Among other things, the SNS dictates the blood flow and the sweat activity. This phenomenon can be leveraged to quantify the psychological or emotional state. This is done by using EDA/Galvanic Skin Response (GSR). EDA measures the skin conductivity of the body. When a person sweats, the conductance of the skin improves. Measuring this allows us to identify episodes of psychological or emotional arousal. The EDA gives a graph of micro siemens over time.

Studies have shown that fatigue can change the activities of SNS [39]. Therefore, observing the system helps to study fatigue.

2.3 Applications of the physiological sensors

Integrating sensors with a computational system allows us to provide solutions for plenty of applications. The sections below chronicles some of the systems that we designed using physiological sensors.

2.3.1 Evaluation Of A Low Cost EMG Sensor As A Modality For Use In Virtual Reality Applications (VR)

This section describes our work on evaluating a low-cost EMG sensor for VR applications. This study evaluates the integration of EMG-based gesture recognition as an input modality for VR applications. Such modalities will help us create studies in VR environments to simulate and study fatigue. This work was published in HCI International 2017 by Gieser, Kanal *et al.* [40].

VR technology is becoming more and more accessible to everyday users. Developers have created immersive applications by blurring the line between reality and VR simulations [41]. Thanks to this accessibility, VR applications have been created for many different fields. Healthcare is one of the fields that has significantly benefited from VR. Applications of VR in healthcare ranges from telemedicine to diagnostics. One way that it helps in diagnostics is to simulate different tests and environments to study different aspects of the body, e.g. fatigue. In most VR applications, the feedback that is provided is in the form of audio or visual. However, when a person interacts with the real world, one of the major forms of feedback is haptics. Haptics involves simulating touch sensation for the user, including the simulation of force, movement, and texture, among others. In many applications, the user often uses a controller to interact with the environment by pressing a button. This feels unnatural and breaks the illusion.

Studies have been done that show the impact of haptics or perceived haptics on fatigue. A study done by Hamam *et al.* was able to deduce a user's fatigue using haptics in a VR environment [42]. They found that they were able to detect this fatigue by analyzing the decrease in the kinetic energy while the user performed a task. Another study done by Taima *et al.* was able to control the user's fatigue using haptics in a mixed reality environment [43]. They found that they were able to reduce fatigue and manipulate physiological reactions using haptics. The results from these studies indicate that it is imperative to eliminate the disconnect between VR and haptics in a VR environment. This allows the use of haptics as a modality to detect fatigue.

One way to improve the accuracy of interaction [44] is to add electromyography (EMG) as an input method. In this paper, the practicality of a low-cost, commercially available EMG sensor in gesture classification is studied. Data was collected from two different EMG sensors. The first is a low-cost Myo bracelet from Thalmic Labs [45], and the second is Trigno Lab [46] developed by Delsys (Figure 2.8). The effectiveness of the low-cost sensor to classify the gestures was studied. For this reason, the results of the low-cost sensors were compared with the results of more expensive sensors.

The main reason for doubts about the practicality of a low-cost sensor is that the sensor does not meet the Nyquist-Shannon criteria [47]. The Nyquist-Shannon criteria specify that the sampling rate of a sensor should be at least twice that of the signal it is sensing. The Myo Armband records EMG data at a sampling rate of 200 Hz. Therefore, due to the Nyquist-Shannon criteria, the armband is able to record the signal below 100 Hz accurately. The frequency range of EMG activity is between 5 to 450 Hz [48]. Therefore, the Myo Armband satisfies the Nyquist-Shannon criteria for the lower end of the EMG spectrum, but it did not satisfy the higher end of the spectrum. On the other hand, the sampling frequency of the Delsys sensor is 1926 Hz [49]. This sensor, therefore, satisfies the Nyquist-Shannon criteria and can be used to evaluate the usefulness of the low-cost sensor.

In order to evaluate the effectiveness of the low-cost EMG sensors as a VR input, a study involving 35 participants was conducted, in which only EMG data were used to check the effectiveness of gesture classification. This will help realize what the user is doing in the virtual space. This study selected the following 11 gestures (Figure 2.9): resting, wave out, wave in, fist, fingers spread, double-tap, pinching, holding up a block, pretending to hold up a block, pointing, and thumbs up. The firmware of Myo armband can already recognize six of these gestures: resting, wave out, wave in, fist, fingers spread, and double-tap.

The data collected by the two sensors were analyzed, and a model was developed for each sensor. Two machine learning algorithms are used: K-Nearest Neighbours (KNN) and Support Vector Machine (SVM). Table 2.1 tabulates the accuracy for both models. The results show that the model created using KNN is more accurate than the model created using SVM. Overall, models created using Myo Armband data performed comparable or better than models created using Trigno sensors. The results from the study indicated that if used properly, there is some validity in using the Myo sensor for VR applications.

The above study lends credence to the use of EMG as a modality to improve haptics. Using such a modality in a VR application helps improve its experience. This helps us create a high-fidelity immersive VR application for fatigue simulation and study.

2.3.2 Apsen: Pre-screening Tool For Sleep Apnea In A Home Environment

As stated before, many illnesses have fatigue as a symptom. One of the most common is sleep apnea [50]. Sleep is very important for human beings. It helps rest our body and mind. Studies have shown a relationship between sleep disorders and fatigue [51]. In this section, we describe a multi-sensory system that we made to detect sleep apnea. The system was intended to be used at home in a familiar sleeping environment and was published in

Figure 2.8: EMG Devices [45, 49, 40]. Myo Armband (Low-cost EMG Sensor), Trigno EMG Sensor (considered as ground truth). The Myo Armband is compared with the Trigno EMG sensor.

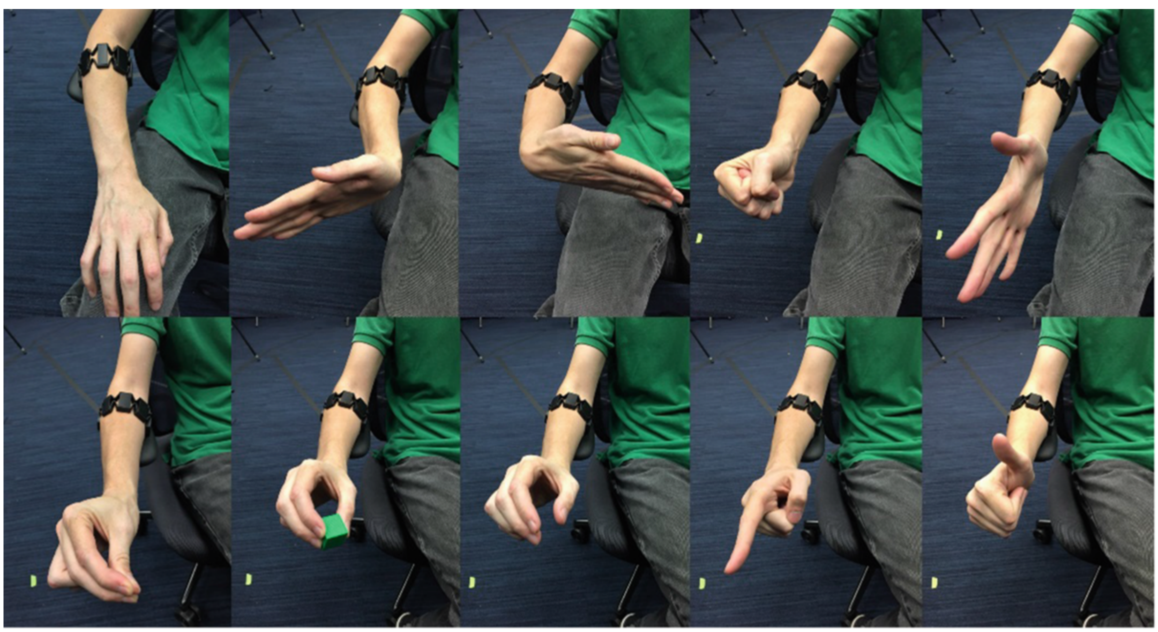


Figure 2.9: The gestures used during data collection. From Top-Left to Bottom-Right: Rest, Wave out, Wave in, Fingers Spread, Pinching, Holding a Block, Pretending to hold a Block, Pointing, and Thumbs up [40]

Table 2.1: Gesture Recognition Performance [40]. The table presents the accuracy for each gesture, model, and EMG sensor. Overall, data from the Myo Armband performed comparable or better than the Trigno Lab EMG sensor. If used properly, the Myo Armband can be used as an input device for VR application

Gesture	Trigno Lab data set		Myo Armband data set	
	KNN	SVM	KNN	SVM
Fist	86.66%	41.11%	95.24%	95.24%
Wave in	94.44%	52.22%	81.43%	81.90%
Wave out	93.33%	48.89%	99.05%	98.57%
Fingers spread	90.00%	46.67%	99.05%	96.67%
Double tap	90.00%	50.00%	98.10%	98.10%
Pinching	83.33%	36.66%	86.19%	92.86%
Pick up block	75.56%	43.33%	87.62%	87.14%
Pretend	84.44%	44.44%	90.95%	92.38%
Pointing	73.33%	48.89%	77.62%	77.62%
Thumbs up	91.11%	43.33%	84.28%	85.24%

HCI International 2017 by Kanal *et al.* [52].

Sleep apnea is a breathing disorder wherein the person's breathing is reduced or completely ceased during sleep. This creates an imbalance in the Carbon dioxide (CO_2)-Oxygen (O_2) levels in the blood. There are three main types of sleep apnea, central, obstructive, and mixed. Central apnea is characterized by a breakdown of communication between the brain and the muscles responsible for breathing [53]. Obstructive apnea occurs when there is an occlusion in the upper airway [54]. During mixed apnea, there is an occurrence of both central and obstructive apnea [55].

In some cases, the position in which the person sleeps also affects the severity of apnea [56, 57]. Due to the obstruction in breathing during sleep, the person wakes up multiple times in the night to break the apnea cycle. This breaks the circadian rhythm leading to a lack of proper sleep. If the person is not well-rested, it will lead to an overall sense of fatigue affecting their health and daily life. According to one report, in 2015, the United States suffered an estimated $150 billion in losses due to undiagnosed apnea [58]. For a person suspected to be suffering from sleep apnea, it is important to detect and monitor it so that precautions can be taken to mitigate its effects. Moreover, monitoring sleep apnea affords us the opportunity to collect contextual information regarding the circumstances under which the fatigue event occurred.

The gold standard for diagnosing sleep apnea is overnight polysomnography (PSG) [59]. In this test, while extracting various physiological data, the patient is monitored by experts in the sleep laboratory. This can cause discomfort and impair the patient's sleep. Since patients do not sleep in their own beds, they may not be able to record their daily sleep habits, which may lead to an underestimation of the severity of apnea.

In this paper, a home apnea detection system, dubbed 'APSEN', was proposed (Figure 2.10). This system uses off-the-shelf, low-cost sensors to detect apnea and the position in which the apnea occurred. The sensors used in this system were a Bluetooth oximeter (SpO_2) (NoninII 9560), a smartwatch (Microsoft Band 2), and an Infrared (IR) camera (Kinect V2). The oximeter was used to detect the apnea, and the Kinect camera was used to classify the sleeping posture.

The apnea detection subsystem uses the SpO_2 signal to detect the onset of apnea. During the onset of apnea, the oxygen in the blood decreases due to the interruption of breathing. In order to classify apnea episodes, this reduction must be 4% or more [60]. To ensure that the apnea episode is valid, the minimum time for the apnea episode was used. If the duration of the apnea episode is 10 seconds or longer; the episode is marked as apnea. To determine the dangerous condition of apnea, SpO_2 was monitored. In healthy people, the normal SpO_2 range is between 95% and 100%. If the SpO_2 value drops below 80% during sleep, it indicates a dangerous condition. The smartwatch starts to vibrate, wake the patient, and terminate the apnea event.

To detect the posture, the Kinect camera was used to monitor the person as they slept. From this camera, IR video was extracted and analyzed in real-time. IR video was chosen as the setup is meant to be used at night while the user is sleeping. The extracted images were then used to classify the posture. Three positions were detected, when the user is sleeping on the back, when they are sleeping on their side facing the camera, and when they are sleeping on their side facing away from the camera. Figure 2.12 shows the different positions. To achieve this, the video frame is passed through a principle component analysis (PCA) algorithm to get the most important features of the video frame. The extracted feature is then used in a machine-learning algorithm to classify the image as per the position in which the person is sleeping. The machine-learning algorithms used are SVM and Convolutional Neural Network (CNN).

Two Graphical User Interfaces (GUI) were designed to be used with the system. Figure 2.13 shows the main GUI designed. Here, the users can connect the sensors. They can also start and stop the system as well as monitor the sleeping subject. Figure 2.14 shows the GUI designed to interact with the position detection system. Here, the user can start and stop the recording. They can also calibrate the system.

To test the apnea detection algorithm data from an online database, PhysioNet was used [61, 62]. The data set consisted of PSG data from 35 participants with varying degrees of apnea severity. Among them, SpO_2 data was extracted from only 8 participants. The data of these participants is used for analysis. Each participant had multiple episodes of apnea during the PSG. The data was annotated for apnea by an expert, which was used as the ground truth. Table 2.2 lists the performance of the algorithm. The results show that the algorithm has high accuracy in determining the absence of apnea, however, the accuracy of determining the apnea state is lower. This indicates that the algorithm had a high specificity.

A study with 10 participants was conducted to create and test posture models. When sleeping in three different positions, 900 infrared images were taken. Table 2.3 shows the performance of the algorithm. SVM and CNN are very accurate in these three positions; CNN is more accurate than SVM. This shows that the system can be used to determine a person's sleeping position.

In this chapter, we discussed the effectiveness of sensors in monitoring physiological conditions. In the following chapters, the study of using physiological sensors to detect and study fatigue will be introduced. Chapter 3 describes a system to identify and study

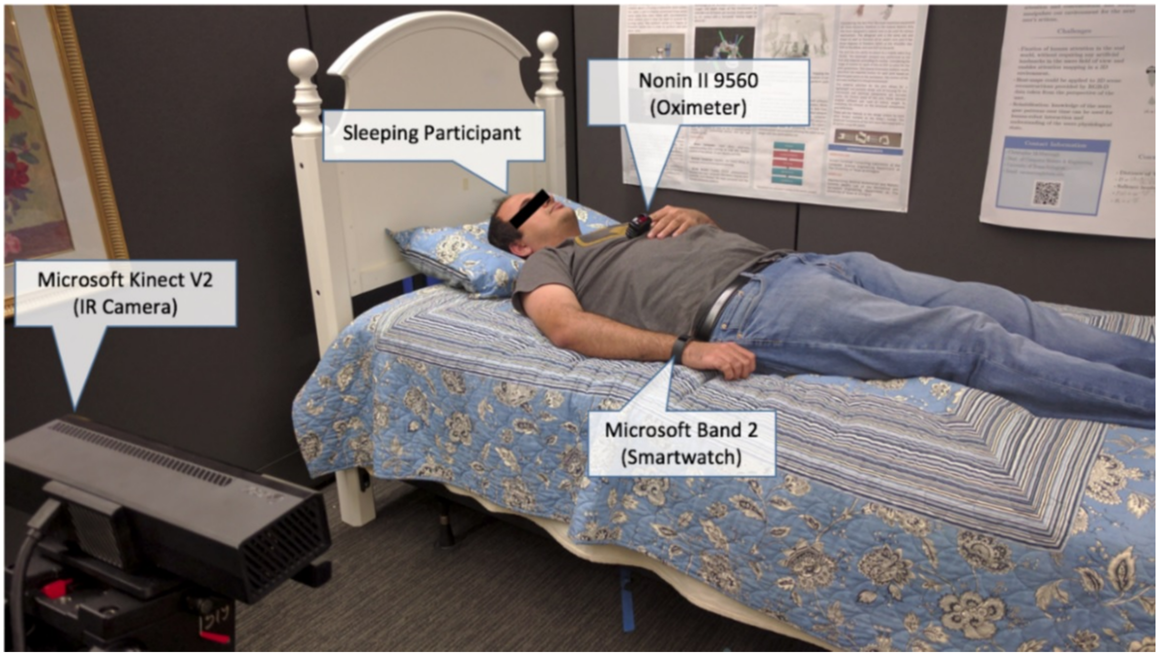


Figure 2.10: APSEN System Setup [52]. The user wears the oximeter and smartwatch and sleeps in front of the IR camera.

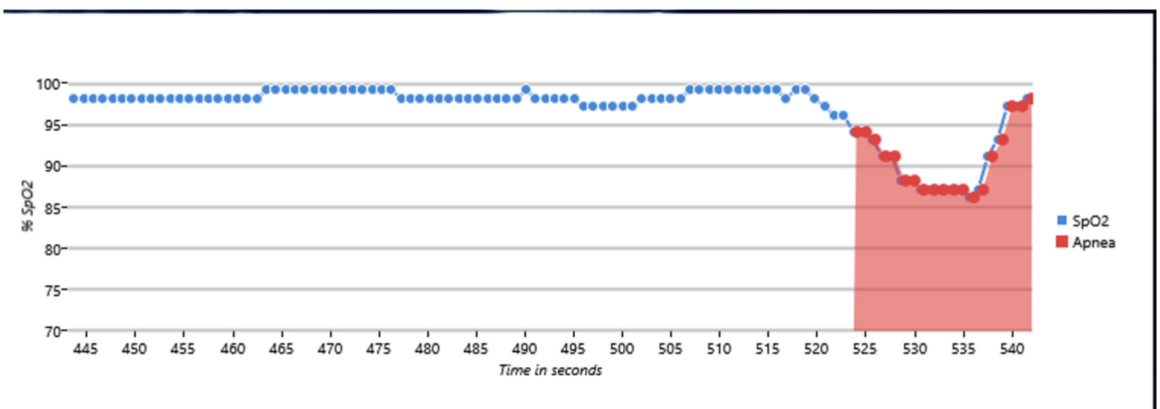
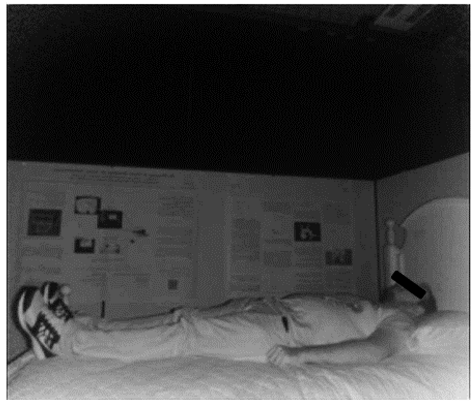
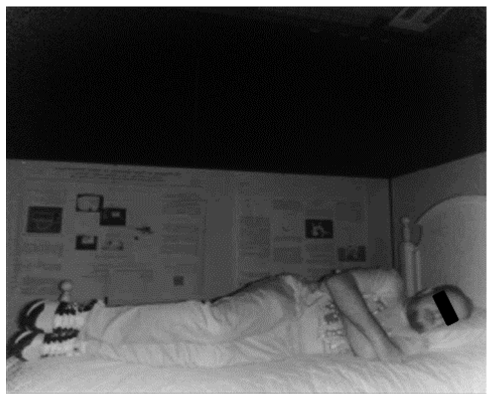


Figure 2.11: Detected Apnea Event [52]. The figure shows the SpO_2 signal over time. Apnea event is detected when SpO_2 falls by 4% or greater.

physical fatigue. Chapter 4 introduces the research on the combination of physical fatigue and cognitive fatigue.



(A)



(B)

(C)

Figure 2.12: Sleeping positions (A) On the Back (B) On the side facing the camera (C) On the side facing away from the camera [52]. Analysis of these positions helps us identify postural apnea.

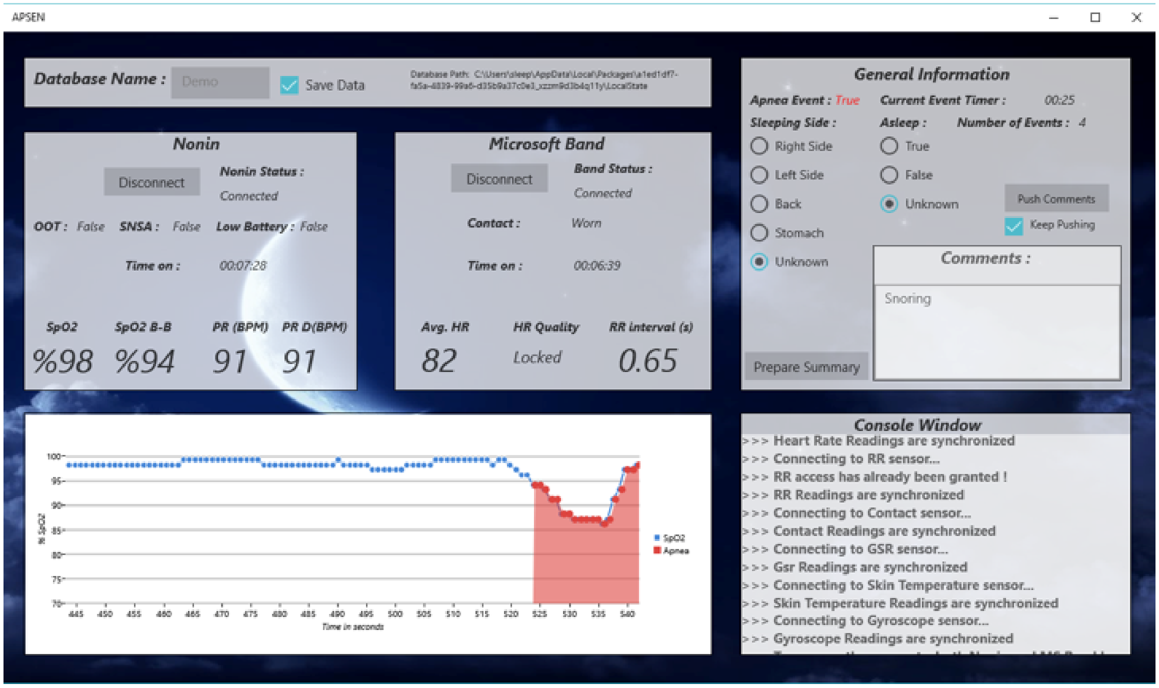


Figure 2.13: APSEN GUI [52]. The user can control the system using this GUI. The GUI provides the ability to connect to the oximeter and the smartwatch (middle two blocks). It also displays the SpO_2 graph in the real time (bottom left block) as well as display the apnea condition. The two blocks on the right provide option to enter user defined annotations if needed.

Table 2.2: Apnea Detection Performance [52]. The table lists the total number of actual Apnea and No Apnea conditions and the number of detected Apnea and No Apnea conditions. It can be seen that the algorithm was able to detect the No Apnea condition at high accuracy. Therefore, the algorithm had a high specificity.

	Ground Truth	Detected	Accuracy
Apnea	1609	1067	66.31%
No Apnea	2338	2278	97.43%
Total	3947	3345	84.74%

Table 2.3: Position Detection Performance [52]. The positions considered are, sleeping on the back, sleeping on the side facing the camera, and sleeping on the side facing away from the camera. The table lists the accuracy of the models designed. It can be seen that both SVM and CNN were able to detect the positions accurately.

	SVM	CNN
Accuracy	74.91%	89.71%

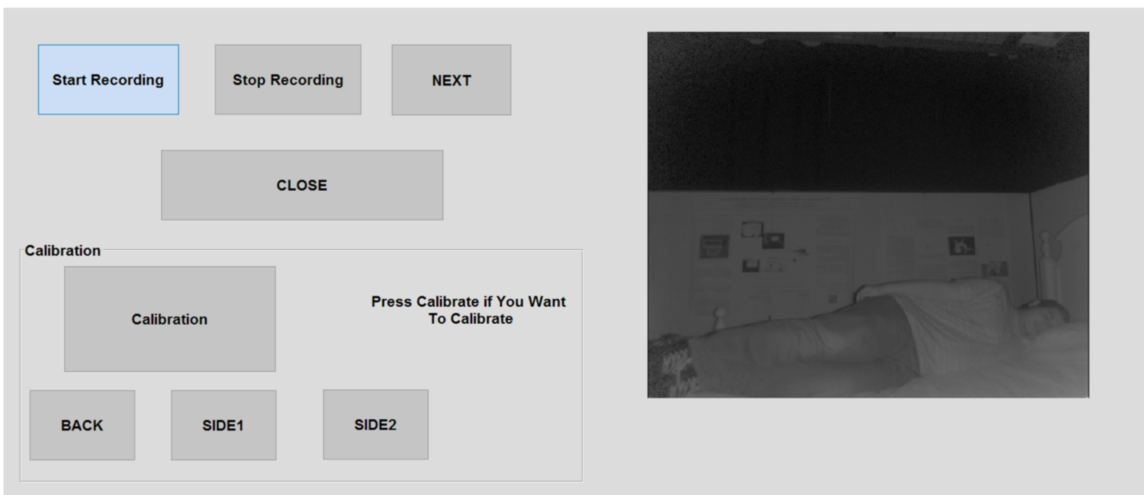


Figure 2.14: Sleeping Position Recording GUI [52]. The user can control the posture detection part of the APSEN system using the controls provided (top left). They can even calibrate the system using the controls at the bottom left. A real-time image is provided on the right to monitor the subject as they sleep.

CHAPTER 3
PHYSICAL FATIGUE AND REHABILITATION

3.1 Introduction

After an injury or a disease/disorder, people may lose some motor functions of their appendages. According to one estimation, in 2013, around 5.4 million people suffered from paralysis in the US [63]. This loss causes a hindrance to their daily life. Simple tasks like tying shoes become challenging. This may be caused by MS, Parkinson's Disease (PD), Traumatic Brain Injury (TBI), and shoulder dislocation, among others.

Due to this, physical rehabilitation becomes an essential step in recovery. In traditional physical rehabilitation, the patient is asked to perform physical exercises designed to use the targeted muscle/muscle group. Repeated usage of these muscles strengthens them as well as train the body to use these muscles again. While they perform these exercises, they are monitored by an expert, such as a physical therapist or rehabilitation expert.

Although traditional rehabilitation is an effective and a very important step towards recovery, it has some drawbacks. It is often labor-intensive to the therapist and not enjoyable for the patient. In rural areas, the patient may have to travel long distances to reach a rehabilitation center. Unfortunately, due to the loss of the motor function of the muscle, it may fatigue easily. This may lead to the patient being unable to perform the exercise anymore, leading to a lengthy rehabilitation process. Due to the fatigue, the subject may also try to compensate by adjusting their stance. This may lead to long-term musculoskeletal issues.

Studies have provided some solutions to the drawbacks mentioned above. Gamified rehabilitation and robotic rehabilitation have been leveraged to address these issues [64, 65, 66]. These methods can keep the patient engaged during rehabilitation [67]. Studies have shown that due to this engagement, the patients have a better chance of retaining the white matter integrity in their brain [68]. White matter is an area of the brain composed of axons of neuronal cells. The primary function of white matter is to transmit information between neurons. Rehabilitation robots can be designed as robotic manipulators [69] or exoskeleton [70, 71].

In this chapter, a system that advanced the research in detecting physical fatigue during robotic rehabilitation is presented.

3.2 Adaptive Robotic Rehabilitation Using Muscle Fatigue as a Trigger

This section describes our work on creating an adaptive rehabilitation system. This work was published by Kanal *et al.* in MobiQuitous 2019 conference [72]. The system designed in this study leveraged robots in an upper-limb rehabilitation scenario. This study allowed us to explore the detection of muscular fatigue in a known context. The rehabilitation exercises performed in this study were purely physical. Therefore, the ambiguity of context was controlled in this study. The study also afforded us the opportunity to implement a method to apply intervention techniques adaptively.

To address the shortcomings of traditional rehabilitation, an adaptive system was designed that would help the patient while they perform the exercise. This system was intended to challenge the patient to perform the exercise and help them if and when needed.

The system was broken down into two parts, the physical exercise and the adaptive element. The hardware used in this study is the Barrett WAM arm [73]. This arm is a 4-Degrees of Freedom (DOF) arm that is capable of applying a considerable amount of force while moving. The patient holds the end-effector of the arm, which is a sphere at the end of the arm, and performs upper limb exercises. The arm was coded in such a way that it was capable of providing two types of forces resistive and assistive. Resistive forces are forces that the subject is working against, and assistive forces are forces that help the hand to reach the goal.

The system was designed to switch between the two forces when fatigue is detected. To achieve this, the system monitors the major muscles responsible for the movement. This muscle/muscle group bears most of the load and thus may fatigue due to the movement. The muscle/muscle group was monitored using a Delsys EMG sensor. This system monitors the muscle during isometric contraction. The isometric contraction of the muscle is where the load on the muscle increases, but the muscle's length remains the same. During this contraction, when fatigue is induced, the median frequency of the EMG signal drops [30, 31, 32]. The system monitors this drop and thus can detect fatigue.

To make the system intuitive and easy to use, two GUIs were designed. The user used these GUIs to interact with the system. Figure 3.3 shows a GUI that is used to design the exercise. The therapist uses the GUI to program the path that the robot must follow. Here, they can also determine the force exerted by the robot. Figure 3.2 shows a GUI that was designed to monitor the fatigue in the subject. This GUI presents the EMG signal and all the derived signals in real-time. It also indicates when the system detects fatigue. Using this GUI, the therapist can monitor the user as well as make an informed decision on the therapy route.

A study was designed to evaluate this system. The participants of the study were asked to perform three physical exercises, Shoulder Flexion (SF), Shoulder Abduction (SA), and Elbow Extension (EE), as shown in Figure 3.1. These are common upper-limb rehabilitation exercises [74, 75, 76]. During SF, the participant holds the robot's end-effector out in front of them and raises it over their head. For SA, the subjects hold the end-effector to their side and raise it to their shoulder level. For EE, the subjects hold the end-effector to their side with their elbow behind them. They will then extend their arm backward. EMG is recorded from the deltoid muscle during SF and SA and from the triceps during EE.

The study had a second objective, to gauge the compliance to the adaptive system. For this, the participants were asked to perform the exercises on the system with and without the adaptive element. The removal of the adaptive element makes the system akin to traditional robotic rehabilitation. The system without the adaptive element is referred to as 'System 1' and the one with the adaptive element is referred to as 'System 2'. The subjects were asked to fill out a survey to provide their subjective feedback after each exercise.

During the study, two time points are recorded, the time when the system detects fatigue and the time when the participants indicate that they are fatigued. The participants were asked to let the experimenter know when they felt fatigued. This time point was then used for analysis. To analyze the performance of the system, these two time points must be as close as possible. For this, an equivalence test, Two One-Sided T-Test (TOST), was performed. This test is an equivalence test and is used to test whether the difference between two numbers is statistically within a certain range. Two null hypotheses were tested. First, the difference between the two numbers is less than the lower limit of the range. The second hypothesis is that the difference between the two numbers is greater than the upper limit. Table 3.1 lists the result of this test. It was found that the system was able to detect fatigue within an error margin of ± 10 seconds of error.

Figures 3.4, 3.5, 3.6, and 3.7 illustrate the results for the surveys performed. The questions asked were designed to extract their subjective experience while using the two systems. It was observed that the subjective fatigue and difficulty level was lower when the participant performed the exercise using the system with the adaptive element. The question in Figure 3.7 was designed to gauge the participant's future probable compliance to the rehabilitation exercise. It was found that the system with the adaptive element had a higher future probable compliance than the one without the adaptive element.

Table 3.1: Temporal Analysis [72]. The table lists the P-Values for the TOST test. The threshold used in the TOST test was 10 seconds. It can be seen that the algorithm can detect fatigue within this threshold.

Exercise	P Value Upper	P Value Lower	Mean Absolute Error (s)
SF	$<0.001^*$	0.008^*	9.444 ± 7.803
SA	0.16	$<0.001^*$	12.646 ± 9.293
EE	0.709	$<0.001^*$	15.311 ± 9.134

* = P Value $<$ 0.05

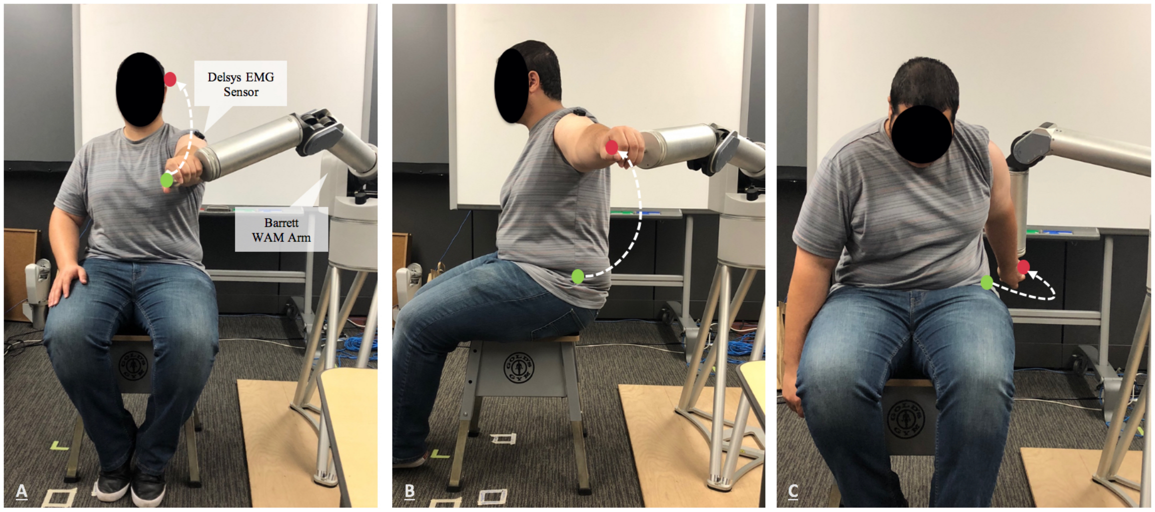


Figure 3.1: Adaptive Robotic Rehabilitation. A user performs three exercises while using the system. The three exercises are Shoulder Flexion (SF) (left), Shoulder Abduction (SA) (middle), and Elbow Extension (EE) (right). The green dot represents the start position. The red dot represents the end position [72]. This system can challenge the user to perform the rehabilitation exercises and help them if and when needed.

3.3 Next Steps

From the above study, we were able to detect muscular fatigue and provide interventions. Inspired by the results from the study, we proceeded to tackle the second type of fatigue, cognitive fatigue. It is important to study cognitive fatigue because it is another severe fatigue that people experience. It is also important to study both types of fatigue simultaneously, as they usually occur concurrently in the real world. The next chapter will introduce the developed system.

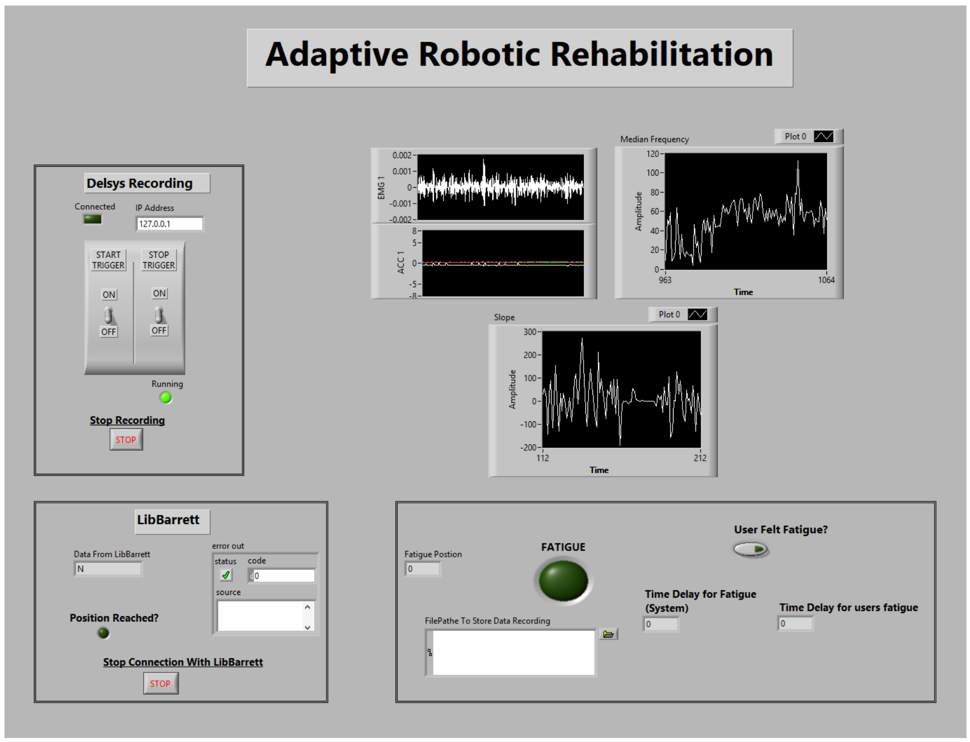


Figure 3.2: Data Acquisition and Fatigue Detection UI [72]. The therapist can monitor the patient using this GUI. The GUI provides buttons to start and stop the recording (left). It also displays the EMG, median frequency, and slope signals (top right). It provides fatigue information (bottom right).

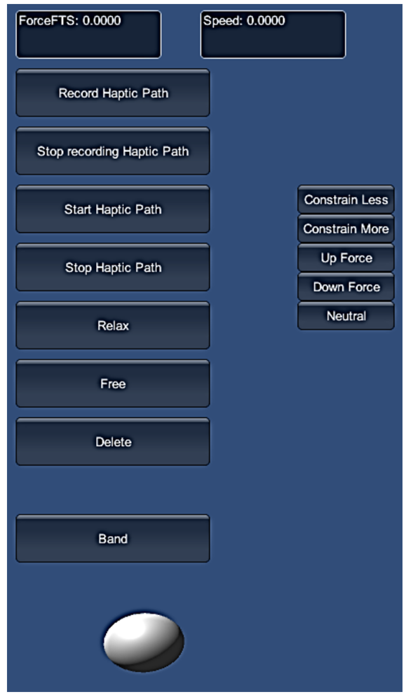


Figure 3.3: Exercise Path Control UI used by the therapist [72]. Using this, they can design the exercise. The GUI provides buttons to set the exercise path (left). It also provides buttons to set the forces applied by the Barrett WAM arm (right). It represents the end-effector of the arm as a sphere (bottom left).

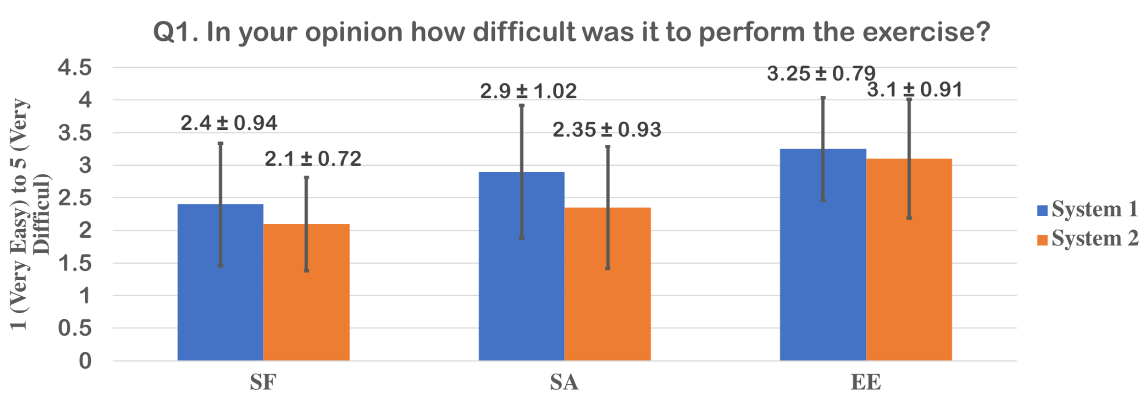


Figure 3.4: Survey Q1: Difficulty Feedback [72]. The figure shows that overall the participants found that the exercises were more difficult to perform with the system without the adaptive element (System 1) than with the system with the adaptive element (System 2).

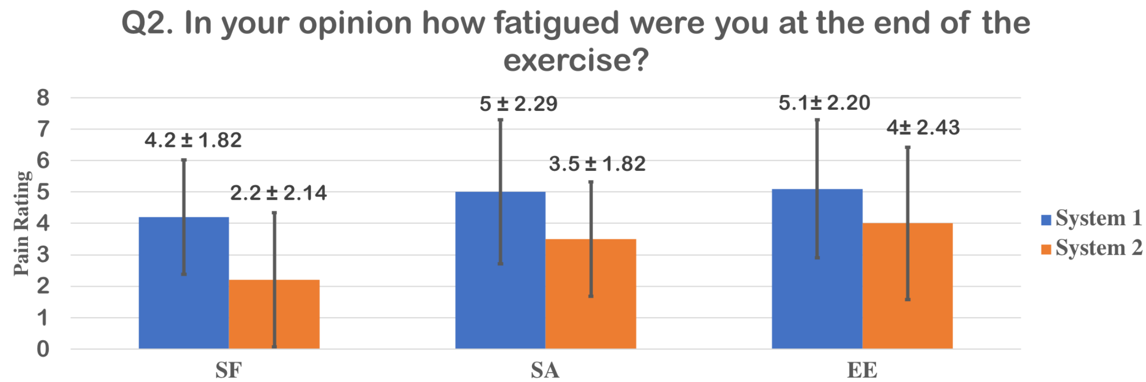


Figure 3.5: Survey Q2: Fatigue Level [72]. The figure shows that overall the participants found that the fatigue experienced was higher in the system without the adaptive element (System 1) than with the system with the adaptive element (System 2). This indicates that the method used to induce physical fatigue was successful.

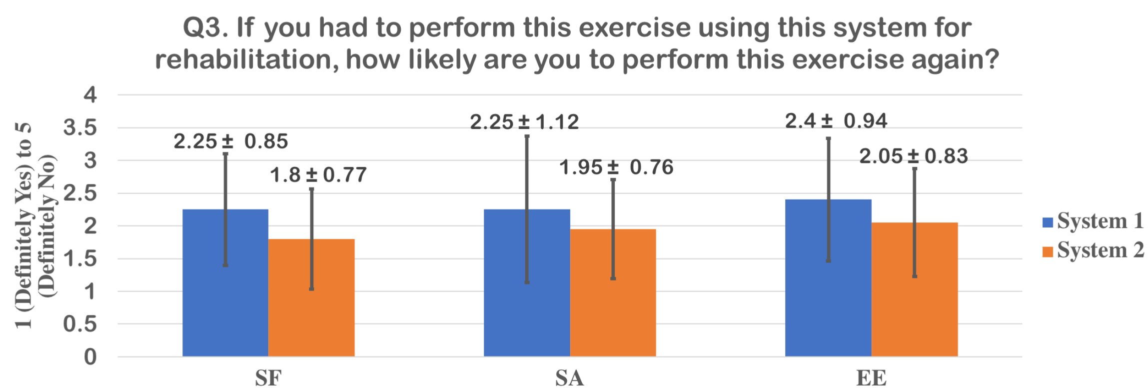


Figure 3.6: Survey Q3: Likely to Perform the Exercise again [72]. The figure shows that the participants were more likely to perform the exercise again with the system with the adaptive element (System 2) than with the system without the adaptive element (System 1). This indicates that the future probable compliance of System 2 is higher than System 1.

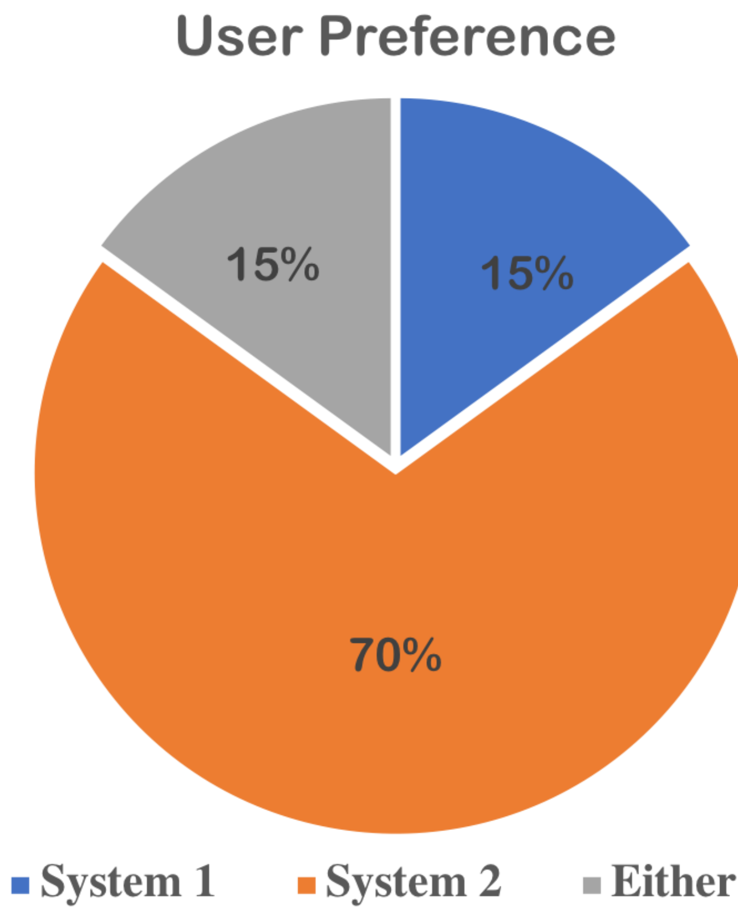


Figure 3.7: Survey Q4: Preference Feedback [72]. Overall the users preferred the system with the adaptive element (System 2) than with the system without the adaptive element (System 1). This indicates that the future probable compliance of System 2 is higher than System 1.

CHAPTER 4

A SINGLE FRAMEWORK TO STUDY PHYSICAL AND COGNITIVE FATIGUE

4.1 Introduction

Previous research focused on detecting physical fatigue and reducing its impact on the rehabilitation process. Subsequent research tried to merge the two types of fatigue into a single structure by first ensuring that physical and cognitive load can be simulated in a controlled environment

The previous study demonstrated a setup and a method to simulate and detect physical fatigue reliably. Using this knowledge, a framework is designed that simulates the two types of fatigue together. Combining the two in a single framework allows us to create experiments that can represent the real world. The framework is flexible enough that it can handle different ways of inducing the two types of fatigue. This is an important property as when we discover a better method to induce the two types of fatigue; it can be easily swapped in the framework.

This chapter outlines research on combining physical fatigue and cognitive fatigue.

4.2 Impact of Physical and Cognitive Fatigue on User Performance: Robot-Based Multimodal Pilot Study

This section describes a framework to combine the two types of fatigue. This paper was published by Rajavenkatanarayanan, Kanal *et al.* at PETRA 2019 conference [77]. Along with providing us the opportunity to combine the two types of fatigue, this study also allowed us to examine a way to induce them.

Like physical fatigue, traditionally, cognitive fatigue is quantified using survey-based methods. Efforts to quantify fatigue using objective measures have been proposed. Physiological signals like EEG have been leveraged to quantify fatigue. This method has shown a high correlation with neurological impairments like MS [78, 79, 80]. Along with quantifying fatigue, these methods have been used to assess cognitive performance and create user-centric tools [81, 82, 83, 84, 85].

A framework was designed to simulate the two types of fatigue by asking the subjects to perform a series of tasks. The system consisted of two parts, a physical setup to induce physical load and a setup to induce cognitive load (Figure 4.2).

The physical setup consisted of a Barrett WAM 4-DOF arm. This arm was coded to position itself to resemble a joystick, as shown in Figure 4.2. The subject would use this to interact with the system by holding the spherical end-effector. The arm was intended to be used only in one plane, the XZ plane with respect to the subject's point of view (Figure 4.1).

This arm interacted with a game running on a screen in front of the subject. This game was dubbed 'FROX' (Figure 4.3). In the game, the subject controls a fox on the screen using the robotic arm. The game would display some berries all around the fox. There were three kinds of berries in the game, strawberry, blueberry, and blackberry. The aim of the game was to collect the berry as per the instruction provided.

The game was designed to induce cognitive load. This was achieved by providing the instruction using the Stroop effect [86]. In this effect, the person has to react to an incongruent stimulus. An incongruent stimulus could be the mismatch between the text identifying a color and the color of the text itself, i.e. 'Red' is written in green font. In the game, the Stroop effect is emulated by providing instruction to the subject to select a berry, but in one of the instructions, the color of the font is not the same as the color of the berry. For example, 'Blackberry' is written in red font. In this case, the subject must identify the error, select the berry corresponding to the color of the font, and select strawberry. Figure 4.4 illustrates the Stroop variation of the FROX game. The framework also had a simple cognitive task against which other cognitive tasks would be compared. In the simple task, the subject had to select the berry as instructed on the screen.

A study of seven participants was conducted to verify the efficiency of the designed system. The study consisted of six stages which are illustrated in Figure 4.5.

- In the first stage, they are required to complete a cognitively simple task. This was used as the baseline.
- In the second stage, physical fatigue was induced. This was achieved by asking the subjects to perform the Shoulder Flexion (SF) exercise similar to the one described in Section 3.2.
- In the third stage, the participants performed the simple task again. The assessment in this stage shows us the effect of physical fatigue on the subject's performance.
- In stage four, the subjects were asked to perform the Stroop task. This stage induces cognitive load.
- At this point, we wanted to make sure that we induced both physical and cognitive load. To this end, in stage five, the subjects were asked to perform the SF task.
- Finally, in the sixth stage, the subjects were asked to perform the cognitively simple task again, which gave an idea of the impact of physical and cognitive fatigue on the subject.

After each stage, the subjects were asked to fill out a survey designed to gauge their state after the tasks. This survey quantified their perceived physical and cognitive fatigue. The subjective difficulty of the task was also extracted from this survey. Apart from these metrics, completion time and task performance were also recorded. Figures 4.6 and 4.7 illustrate the responses.

It can be seen from the figure that the subjective fatigue between Stage 1 and Stage 6 increased, but when analyzing the results of the participants, it was found that in Stage

6, subjects received higher scores. In these stages, the subjects performed the cognitively simple task. Stage 1 is the baseline stage, and Stage 6 is the stage after physical and cognitive fatigue. The difference in performance indicators may be due to the way the two types of fatigue interact with people, or it may be due to the insufficient challenge of the cognitively simple task.

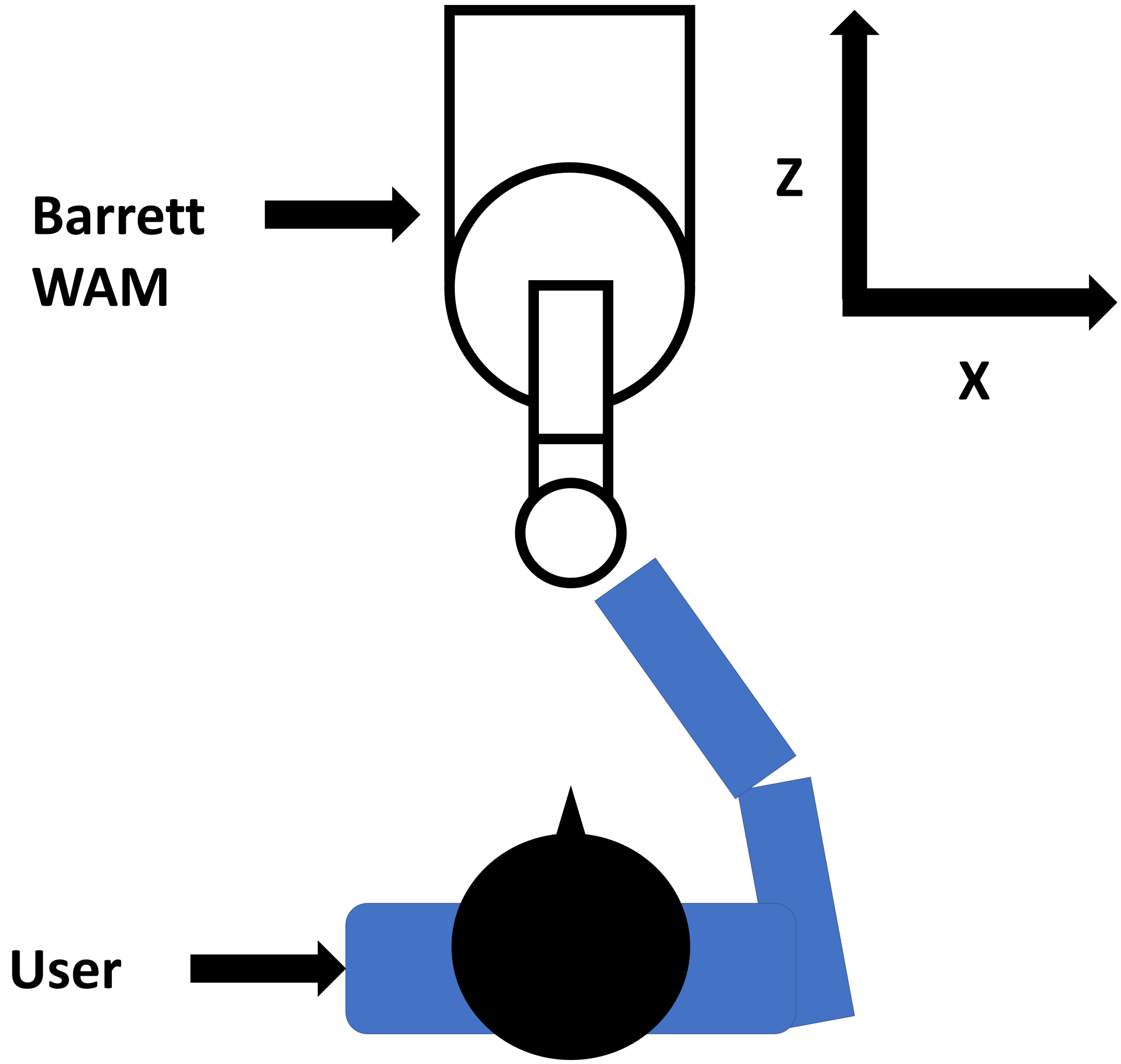


Figure 4.1: Hardware Coordinate Space (Top View). The user moves the robotic arm in the XZ plane. Using this robot, the user controls a character on the screen.

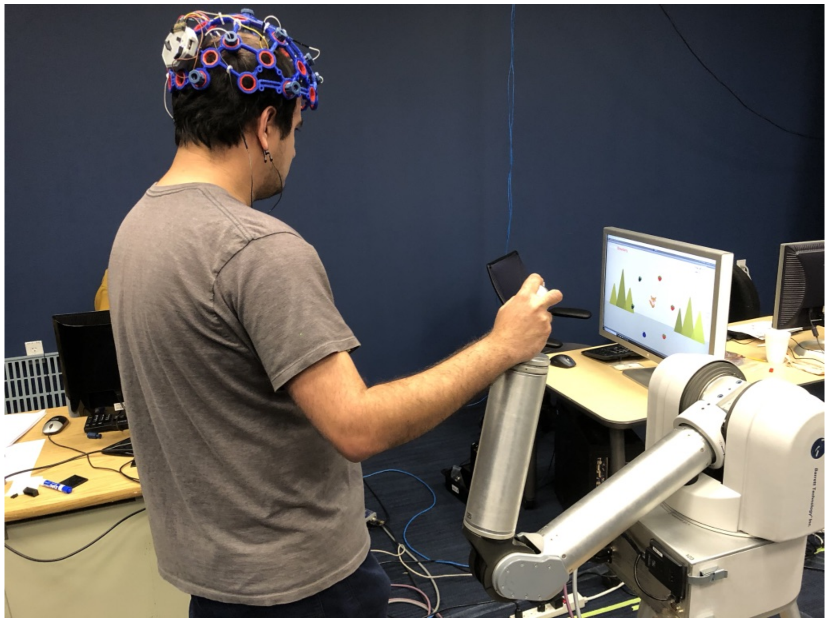


Figure 4.2: A user playing the Frox game [77]. This game, along with the overall system, is designed to induce physical and cognitive fatigue. The user controls the arm using the end-effector and moves a character on the screen.

a b

Figure 4.3: Frox game [77]. The user controls a fox on the screen (center) surrounded by berries. When instructed (top left), the user catches the appropriate berry. The task shown in the figure is the simple task against which the other tasks are compared.

4.3 Human-Robot Game-based Assessment of Physical and Cognitive Fatigue.

This section describes the updated version of our previous framework. The previous framework utilized the Stroop Test to induce cognitive fatigue. As postulated earlier, this may not have been sufficient to challenge the user. Moreover, the user was able to move the arm without resistance. The updated framework addresses these issues. This work was

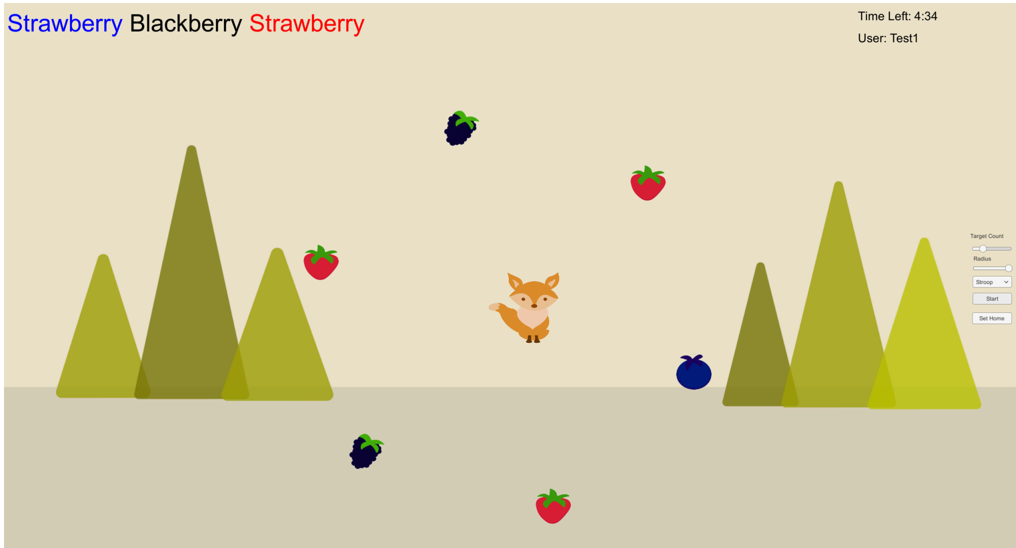


Figure 4.4: Variation of the Fruits and Fox game to induce cognitive fatigue through Stroop effect [77]. The Stroop effect is emulated through the instruction provided (top left). When instructed, the user must control the fox (center) and catch the appropriate berry. In this example, the user must recognize that strawberry is written in blue color in the instruction. Therefore, the fox must catch the blueberry.

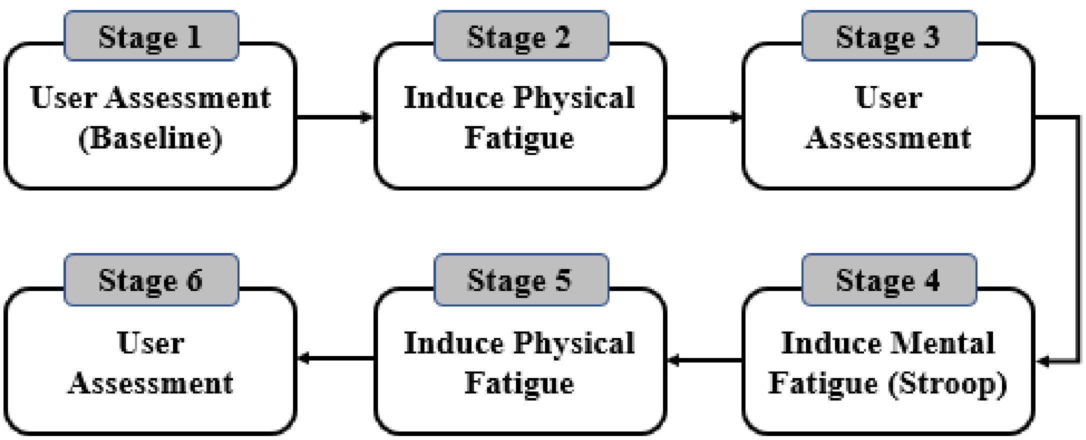


Figure 4.5: Study Protocol to evaluate the Frox system [77]. In stage 1, the user performs the baseline task. In stage 2, physical fatigue is induced in the user. In stage 3, the user performs the baseline task again. In stage 4, mental fatigue is induced through the Stroop variation of the game. In stage 5, physical fatigue is induced again. In stage 6, the user performs the baseline task again. Using this protocol, we were able to induce and study both physical and cognitive fatigue.

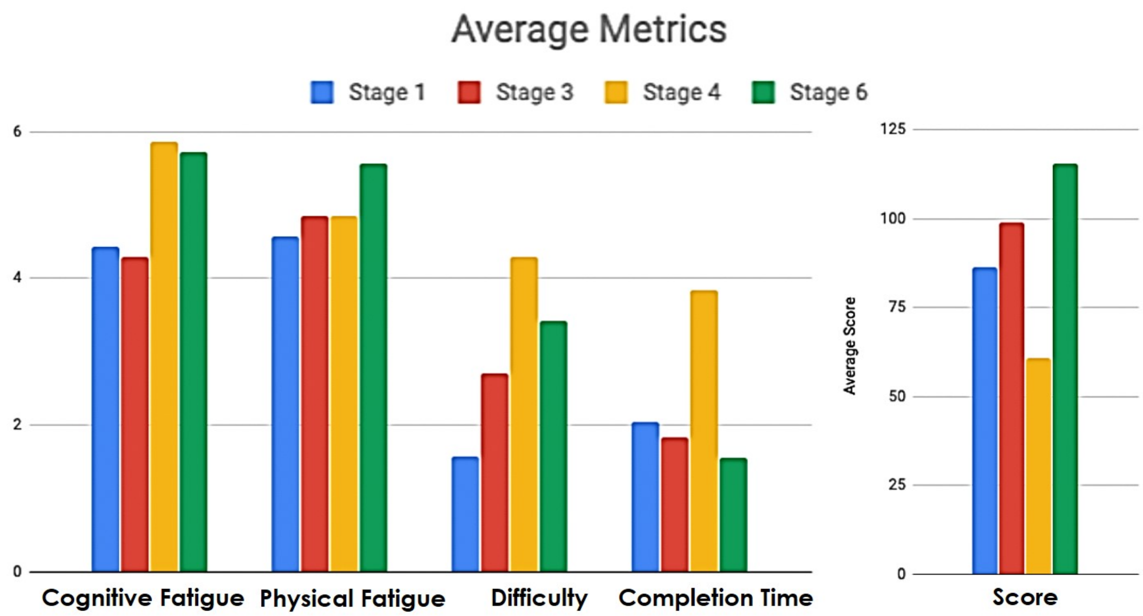


Figure 4.6: Average survey and score metrics for each task [77]. It can be observed that the cognitive and physical fatigue increased between the phases indicating that subjectively the setup was able to induce fatigue. Between stage 1 and stage 6, even though cognitive fatigue increased, the score improved. This indicates that the task used to measure fatigue objectively may not have been sensitive enough.

published by Kanal *et al.* at PETRA 2020 conference [87].

To address the limitation of the previous study, an updated framework was proposed which combined physical and cognitive fatigue. Like the previous framework, the updated framework tried to simulate fatigue by asking the subject to perform a series of tasks. This framework consisted of two parts, a physical setup to induce physical fatigue and a setup to induce cognitive fatigue.

The updated setup (Figure 4.8) induces physical fatigue by asking the subject to interact with a Barrett WAM arm set up in a joystick-like position. One drawback of the previous setup was that the subjects were able to move the arm freely in the XZ plane (Figure 4.1) without resistance. Even though the subjects performed physical work while interacting with the robot, the robot did not challenge the subject while doing this work. To address this, the robot in the updated framework allows the arm to move in only four directions,

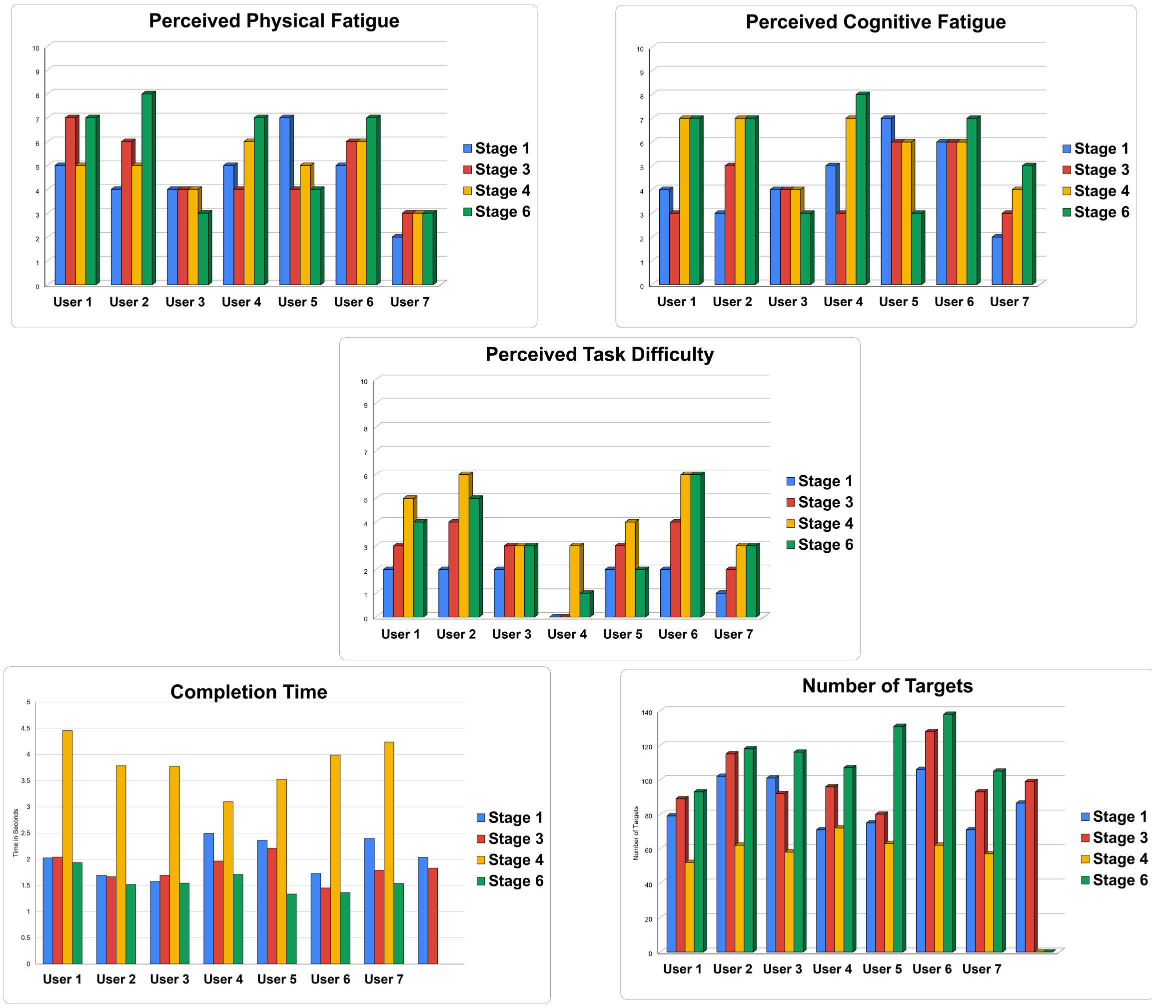


Figure 4.7: User survey and performance results. (a) physical fatigue, (b) cognitive fatigue, and (c) task difficulty for all users. We also visualize the objective measures of (d) completion time and (e) task performance (number of targets reached) [77]. The results for individual user analysis echo the results obtain from the analysis shown in Figure 4.6

forward, backward, left, and right. These four directions were restricted in the XZ plane with respect to the subject's point of view. When the subject tries to move in any of the allowed directions, the robot will provide some resistance to the movement. This resistance increases as the subject move further from the center. This ensures that the subject performs physical work while interacting with the system.

The subjects use the arm to interact with a character in a game designed to induce cognitive fatigue. The designed game was a 'dungeon crawler' dubbed 'Escape the Knight'

(Figure 4.9). In this game, the subject controls a character on the screen trying to evade a knight by solving a maze. The maze consisted of randomly generated rooms with four doors on each end. The subject is asked to choose a door based on the instruction provided by a wizard on the screen. In this game, the wizard provides instruction based on the N-Back test [88]. In the N-Back test, subjects are provided instruction in a sequence. If the current instruction is the same as the instruction provided 'N' steps back, then the subject has to execute that instruction. As the 'N' increases, the level of difficulty and cognitive load on the subject increases.

A study was conducted to test the system. Twenty participants were considered in this study which consisted of three phases. Figure 4.10 illustrates the protocol of this study. In the first phase, the subjects were asked to perform a cognitively simple task. This task is the 0-Back task, where the subjects are provided with directions in a series. They would move in the direction instructed as soon as instructed. In the second phase, physical fatigue is induced by asking the subjects to perform the EE exercises similar to the one in Section 3.2. In the third phase, the subjects are asked to perform the 2-Back task. In this task, the subjects are provided with directions in a series. They must move in the provided direction if it is the same as the one provided two steps back.

After each phase, the subjects are asked to fill out a survey, which extracts their state after the tasks. The survey quantifies subjective mental fatigue and tiredness. It also quantifies how sleepy and active they feel as well as how difficult they found the task to be. Apart from these, the performance in terms of the score is also recorded. Figures 4.11, 4.12, and 4.13 illustrate the responses. An Analysis of Variance (ANOVA) test with multiple comparisons was performed on the survey result to analyze the changes between different phases. The ANOVA test is a statistical test used to determine whether a group of two or more data sets is statistically different. To this end, it analyzes the variance between and within groups. A paired T-Test was done on the score and mental fatigue between phases one and three. Paired T-Test is a statistical test used to determine whether a group of two paired data sets is statistically different. Paired data sets are sets that have a common link between them. For example, Group A contains data collected from 10 subjects, and Group B contains data collected from the same subjects, in the same order, after they were given medication. The T-Test achieves this by analyzing the mean of the difference between the two data sets.

To study the relationship between the survey results and the score obtained from the game, Kendall's and Spearman's correlation tests were performed. The correlation test is a statistical test used to analyze the relationship between two groups. These tests give a correlation coefficient in the range of -1 to 1. 1 is a perfect direct correlation, which means that if the value in one group increases, the value in the other group also increases. -1 represents a perfect indirect correlation. This means that if the value in one group increases, the value in the other group decreases. 0 means no correlation. Kendall's and Spearman's correlation tests are non-parametric rank-based correlation techniques. Unlike other correlation techniques, these do not assume a normal distribution of the data. A test for normality, Kolmogorov-Smirnov test, was performed. In this test, the null hypothesis is that the data follows the normal distribution, while the alternate hypothesis is that the data does not follow the normal distribution. As seen from Tables 4.4 and 4.5, neither the survey nor the score data follow a normal distribution. Therefore, Kendall's and Spearman's correlation tests were chosen to analyze the relationship between the survey results and the score.

Tables 4.1, 4.2, and 4.3 show the results of the statistical tests performed on the survey questions. It has been found that this system can cause physical fatigue and cognitive fatigue. Table 4.6 and Table 4.7 show the correlation coefficient between the survey results and performance indicators. The results show that the link between subjective mental fatigue and the score is weak, suggesting that performance may not be sufficient to measure and detect fatigue.

Table 4.1: Score Paired T-Test 0-Back vs 2-Back [87]. It can be seen that there was a significant difference in the score between the 0-Back and the 2-Back tasks.

Score	
0-back vs 2-back	$1 * 10^{-5}*$

* = P Value < 0.05

Table 4.2: Mental Fatigue Paired T-Test 0-Back vs 2-Back [87]. It can be seen that there was a significant difference in the subjective reporting of mental fatigue between the 0-Back and 2-Back tasks indicating that the subjective mental fatigue was induced.

Mental Fatigue	
0-back vs 2-back	0.002*

* = P Value < 0.05

Table 4.3: ANOVA and Multiple Comparison for Survey Results [87]. It can be observed that the subjective reporting of tiredness between Phase 2 and Phase 3 was significantly different. Moreover, it can also be seen that the subjective difficulty between all the phases was significantly different.

	Tired	Sleepy	Active	Difficulty
ANOVA	0.14	0.22	0.45	0.005*
Phase 1 vs Phase 2	0.11	0.32	0.72	$7 * 10^{-4}*$
Phase 1 vs Phase 3	0.92	0.74	0.02	$1.58 * 10^{-5}*$
Phase 2 vs Phase 3	0.03*	0.30	$0.008*$	0.03*

* = P Value < 0.05

Table 4.4: Test For Normality: Score [87]. It can be seen that the score value for both tasks did not follow a normal distribution.

	P-Value
0-Back	$4.72 * 10^{-19}$
2-Back	$4.72 * 10^{-19}$

Table 4.5: Test For Normality: Survey [87]. It can be seen that the question regarding the participant's subjective feeling of being active followed a normal distribution in Phase 1. All other questions did not follow a normal distribution for either phase.

Question	Phase 1	Phase 3
Difficult	$1.30 * 10^{-13}$	$3.25 * 10^{-18}$
Mental	0.04	$1.04 * 10^{-4}$
Tired	0.01	0.02
Sleepy	0.04	0.01
Active	0.13*	0.004

* Normal

Table 4.6: Kendall Correlation between Survey Answers and Score [87]. The table lists the correlation coefficient for the test. It can be seen that there is a weak relationship between subjective reporting of mental fatigue and the score, indicating that the performance measure may not be a good measure to detect fatigue.

Kendall				
	τ		P	
	0-back	2-back	0-back	2-back
Difficult	0.15	-0.12	0.47	0.52
Mental	-0.04	0.36*	0.88	0.04*
Tired	-0.04	0.18	0.88	0.33
Sleepy	-0.06	0.32	0.80	0.07
Active	-0.09	-0.05	0.69	0.81

* = P Value $<$ 0.05

Table 4.7: Spearman Correlation between Survey Answers and Score [87]. The table lists the correlation coefficient for the test. It can be seen that there is a weak relationship between subjective reporting of mental fatigue and the score, indicating that the performance measure may not be a good measure to detect fatigue.

Spearman				
	ρ		P	
	0-back	2-back	0-back	2-back
Difficult	0.17	-0.14	0.47	0.54
Mental	-0.05	0.44	0.83	0.05*
Tired	-0.05	0.22	0.81	0.35
Sleepy	-0.07	0.40	0.77	0.08
Active	-0.10	-0.02	0.65	0.92

* = P Value $<$ 0.05

4.4 Problems, Limitations, and Observations

In the past two chapters, we discussed systems designed to detect and integrate the two types of fatigue. In the first system (Section 3.2), we were able to detect physical fatigue and provide intervention when needed. Through the following two systems (Sections 4.2 and 4.3), we found an indication of the successful integration of the two types of fatigue, but there are limitations. One major limitation of our systems was that we focused on muscular fatigue rather than overall fatigue. In applications like rehabilitation identifying and accounting for muscular fatigue is important, but for diagnosis, it only gives half of

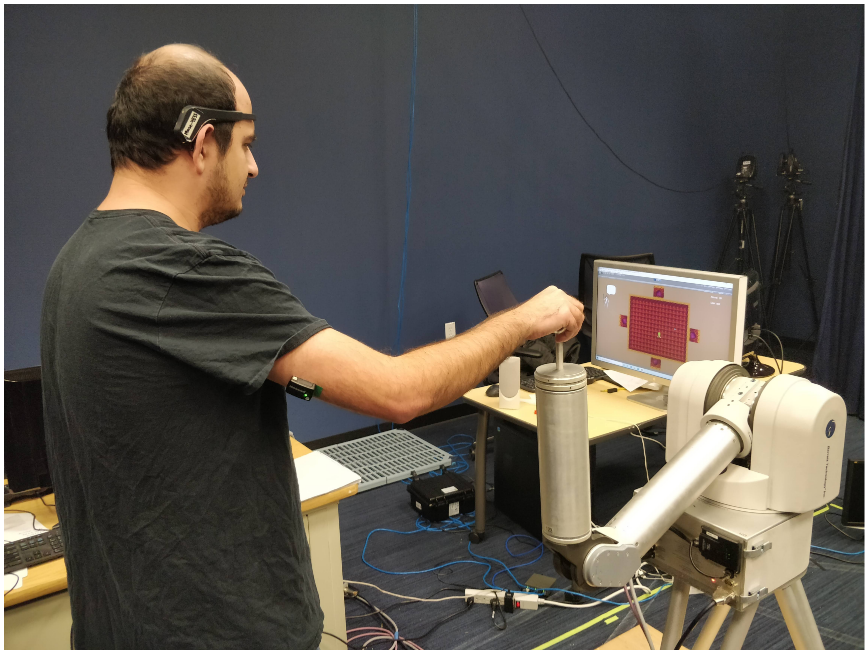


Figure 4.8: A user playing the Escape The Knight game [87]. This game, along with the overall system, is designed to induce physical and cognitive fatigue. The user controls the arm using the end-effector and moves a character on the screen.

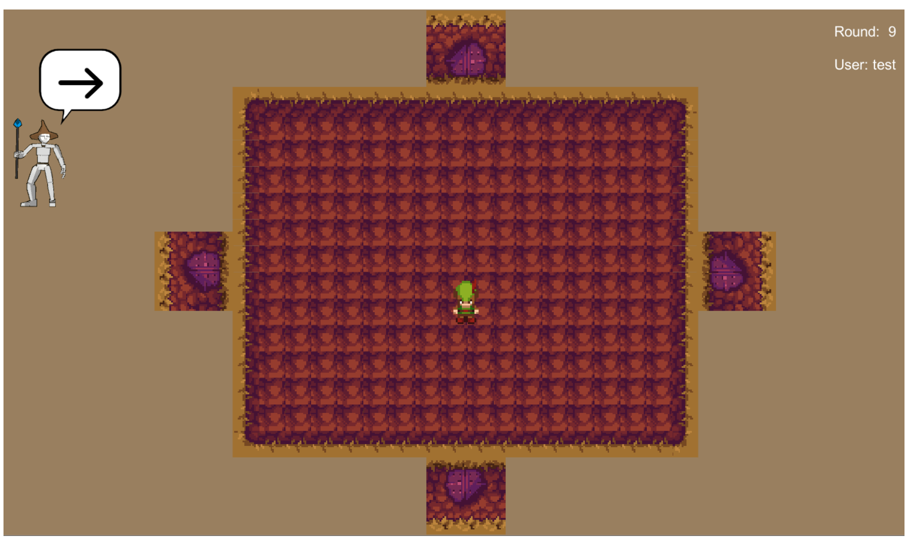


Figure 4.9: Escape The Knight game [87]. The user controls a character (center) surrounded by four doors. A wizard on the screen (top left) gives instructions to the user based on which the user must choose the door. Using this game, we can induce cognitive fatigue by emulating the N-Back task.

the picture. Through the studies, we saw a weak relationship between performance and subjective fatigue. Inducing overall fatigue may provide a better insight into leveraging the

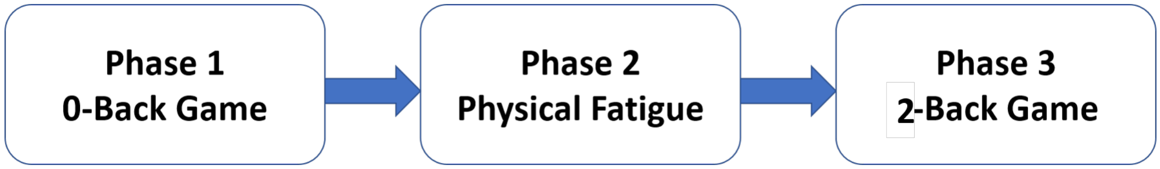


Figure 4.10: Study Protocol to evaluate Escape The Knight system [87]. In phase 1, the user is asked to play the 0-Back version of the game. In phase 2, physical fatigue is induced. In phase 3, the user is asked to play the 2-Back version of the game. Through this protocol, we can induce and study physical and cognitive fatigue.

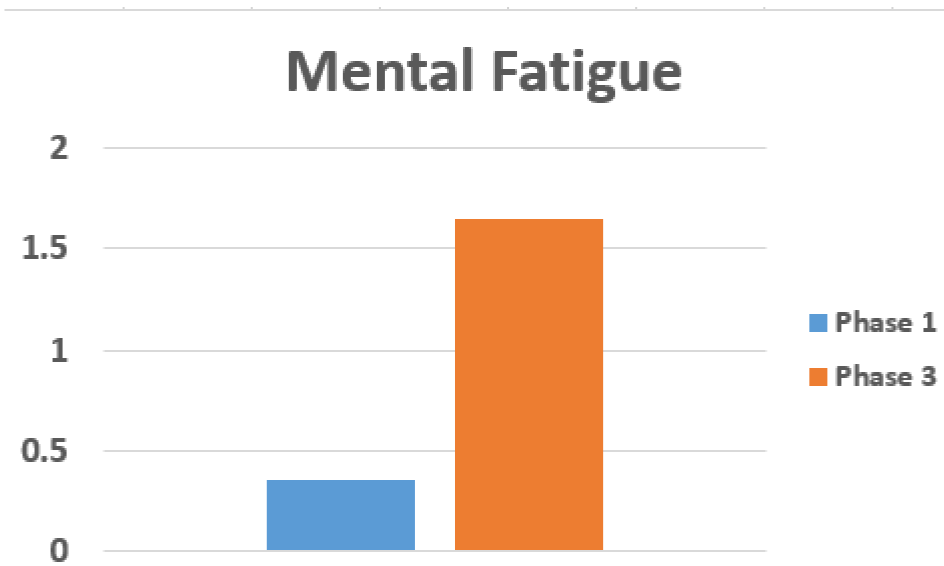


Figure 4.11: Mean Mental Fatigue for Phase 1 and Phase 3 [87]. It can be observed that subjective mental fatigue increased between phases 1 and 3, indicating that fatigue was induced using the method employed.

interaction between the two types of fatigue to detect them together.

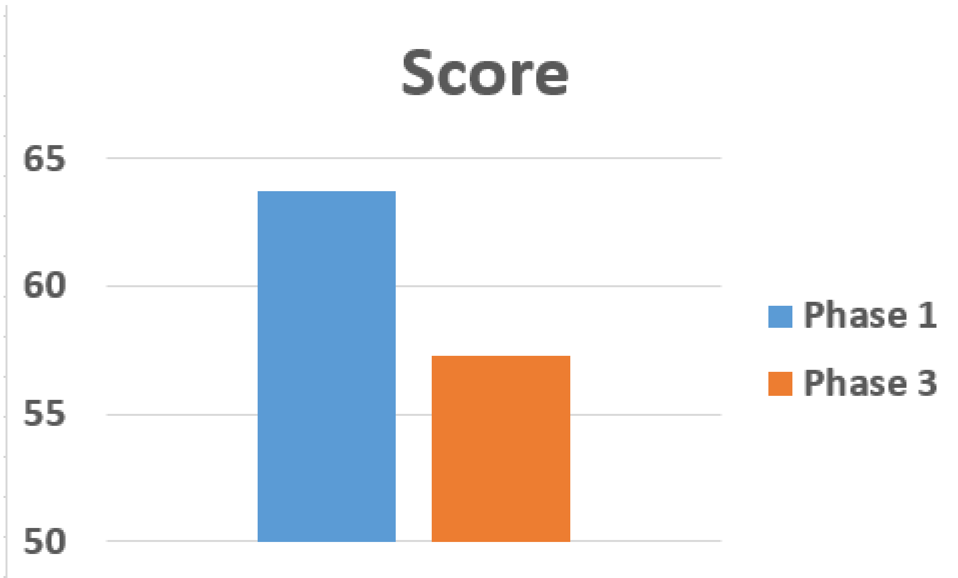


Figure 4.12: Mean Score for Phase 1 and Phase 3 [87]. It can be observed that the score decreased between phases 1 and 3.

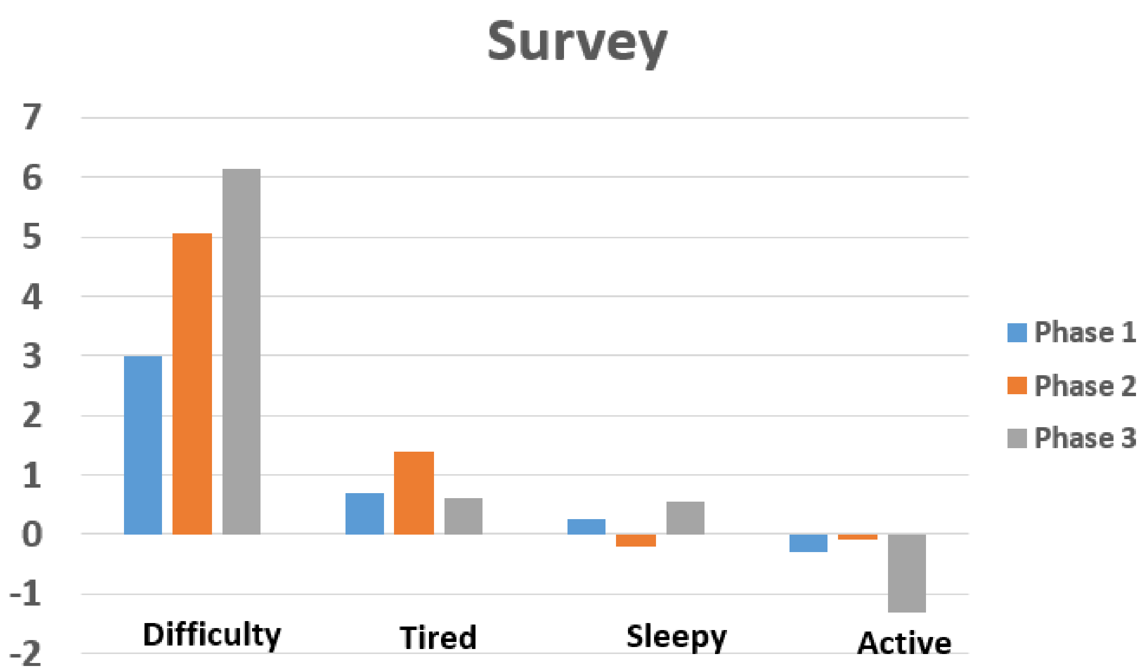


Figure 4.13: Mean Values for Survey [87]. It can be observed that the subjective difficulty increased between phases 1 and 3. This provides a possible explanation for the result observed in Figure 4.11. In other words, the increase in mental fatigue may have been influenced by the increase in task difficulty.

CHAPTER 5

THE KOPOS SYSTEM

5.1 Introduction

The previous chapters discussed the proposed systems made to quantify individual fatigue. Although it is important to examine these two types of fatigue separately, it does not reflect how fatigue occurs in the real world. Many tasks performed in the real world may require physical and cognitive skills. Therefore, to accurately establish a fatigue model, it is important to study both types of fatigue at the same time.

To achieve this, a system is proposed that provides a platform to simulate these two types of fatigue and study them. The proposed system is dubbed KOPOS, which is Greek for fatigue or strain. This chapter discusses the design and the framework of the KOPOS system.

5.2 Sensors

In order to create a system that can detect and study physical and cognitive fatigue in the same setup, it requires the ability to (1) identify contextual changes that may trigger an instance of fatigue and then (2) monitor, correlate and analyze changes occurring in the human body so that a better understanding is obtained of a person's reaction to his/her environment. To make such an intelligent system, physiological sensors are employed. These sensors allow the system to monitor the current state of the human body.

Fatigue is a complex phenomenon. It affects multiple systems of the body. Fatigue can affect the cardiovascular system, the endocrine system, and the brain, among others. Due to this, monitoring only one aspect of the human body would not provide the whole impact of fatigue. To monitor multiple systems of the body calls for a multi-sensory approach.

Using such an approach gives a bigger picture of the fatigue and provides more accurate insights to the experts on how to treat it.

Figure 5.1 lists the sensors used in this system. The following data are extracted in this system by using the sensors explained in Chapter 2.

- ECG
- EDA
- EEG
- EMG
- SpO_2
- Breathing Sounds
- Respiration

The data listed above provide a measure of the different subsystems in the body. ECG indicates the changes in the cardiovascular subsystem. Respiration data, breathing sound, and oximeter provide a measure of the mechanical and functional aspects of breathing. EDA provides a measure of the sensory response to fatigue. EMG gives us an indication of the muscular response to fatigue. EEG gives a measure of brain activity. Using this multi-sensing information, we use a more holistic approach to detect fatigue. This information also allows us to detect both types of fatigue as they affect different combinations of subsystems. To collect these data, a sensing platform called Biosignalsplux [89] is employed. Figure 5.3 shows the Biosignalsplux platform, which consists of multiple sensors that communicate with a central hub. ECG, EDA, EMG, SpO_2, and breathing data are extracted from this platform. The ECG sensor is configured to the Lead II setup of the Einthoven's triangle. EDA is extracted from the right shoulder. EMG is extracted from the leg. SpO_2 is extracted from the right index finger. Respiration data is extracted using a

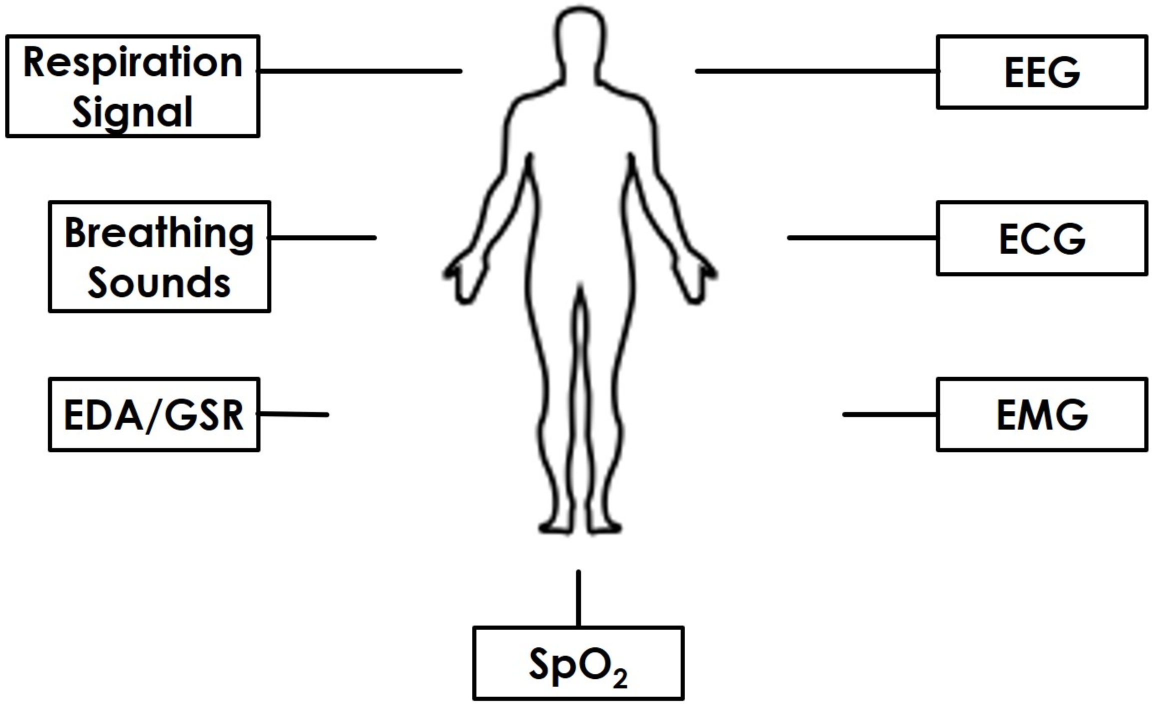


Figure 5.1: Sensors used in the KOPOS system. The system uses ECG, EMG, EDA/GSR, EEG, SpO_2, Breathing Sounds, and Respiration signals. The KOPOS system uses this multi-sensory setup to detect and study fatigue.

breathing band strapped to the chest of the subject. This provides the mechanical data for thoracic breathing. Figure 5.6 illustrates the positions where the sensors are attached.

To extract the EEG data, the MUSE [90] sensor is employed. The MUSE sensor is an EEG Sensor shaped like a headband. Figure 5.4 shows the MUSE sensor. This sensor records data from the frontal and the temporal lobe. It records data from the TP9, TP10, AF7, and AF8 locations on the 10-10 EEG system. Figure 5.7 shows the position of the four sensors on the MUSE.

To record breathing sounds, a data collection system is made using microphones and an Arduino Nano microcontroller development board [91]. Figure 5.5 shows the designed platform. Four microphones are connected to the microcontroller. This microcontroller records data from the microphones and transmits it over the USB. The microphones are attached at the suprasternal notch, xiphoid process, and on the left and right lung. Table 5.1

lists all the sensing platforms and the sensors used in the KOPOS system.

To make the sensor attachment easier, a sensor suit is designed. This suit is made using a stretchable Under Armour shirt [92]. The sensors are embedded within the suit. The sensors are hidden behind a detachable covering so that it can easily be removed for washing the suit. Figure 5.2 shows the prototype of the suit.

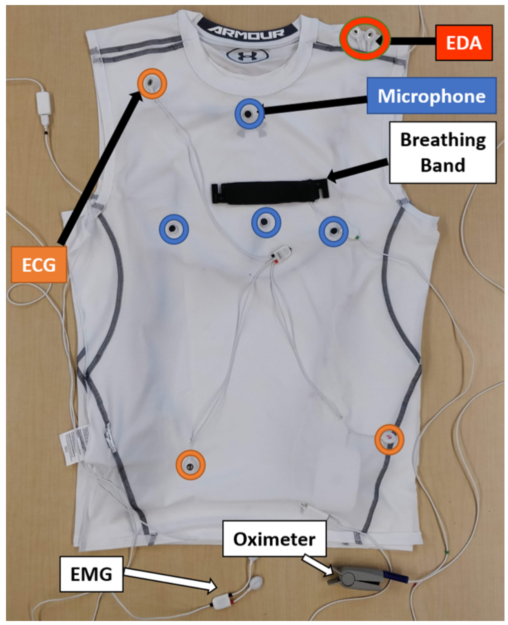


Figure 5.2: The prototype of the Sensor Suit (Inside Out View) [93]: Sensors are embedded in the shirt, which will be in contact with the user's torso. This sensor suit can provide us with the necessary data while the user is performing different tasks and, therefore, help study the relationship between the detected fatigue and the individual's physiological state over time.

Table 5.1: List of the sensing platform used in the KOPOS system. The table also lists the sensors used from each platform

Sensing Platform	Sensor
Biosignalsplux	ECG EMG EDA SpO_2 Respiration
MUSE	EEG
A platform built using Arduino Nano	Breathing Sounds

Figure 5.3: Biosignalsplux sensing platform [89]. This sensing platform is used to record ECG, EMG, GSR, SpO_2, and Respiration Signal. The data extracted from these sensors help us study both physical and cognitive fatigue.

5.3 System Architecture

The system can be divided into four main parts; data extraction, feature extraction, machine learning, and user feedback. Figure 5.8 provides an overview of the system. The user attaches the sensors to their body using the sensor suit designed. The sensor suit communicates with a computer that runs a program for the data collection. To analyze the data first features are extracted from them. These features define the data and are then used for classification.

One important aspect of studying fatigue is the context in which it is studied. For example, if the person is performing a purely physical task, it is more apt to analyze physical fatigue. If the task is purely cognitive, then it is apt to analyze cognitive fatigue. Finally, if the task requires both physical and cognitive effort, it is prudent to study both types of

Figure 5.4: MUSE [90] EEG sensor. The user places this sensor on the forehead while playing the cognitive game. This sensor is a nonobtrusive and compact sensor and thus was used to make the system simple and intuitive. The EEG data is extracted from the sensor, which is then used to study cognitive fatigue.

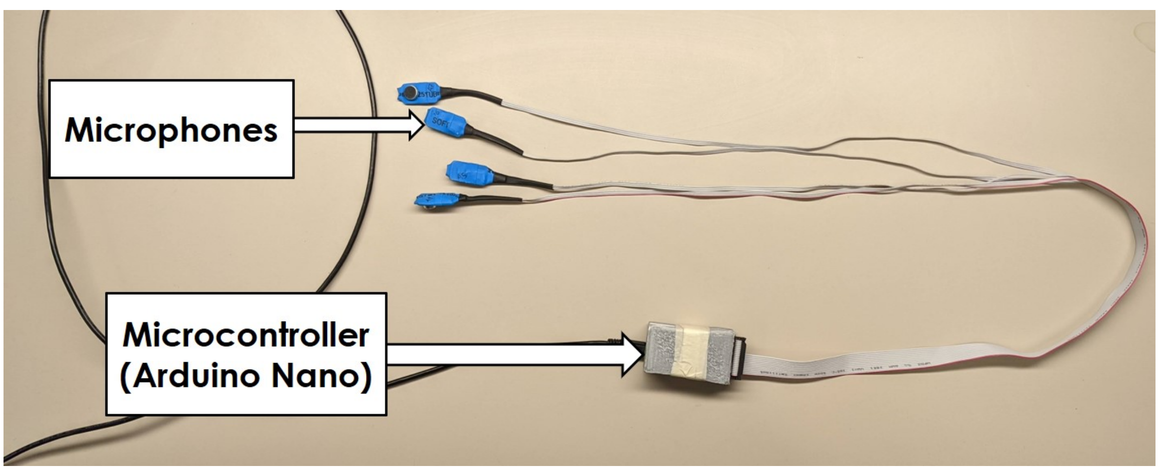


Figure 5.5: Breathing Sound Recording Setup. The setup consists of microphones communicating with an Arduino Nano microcontroller. The microphones are attached to the torso to record the breathing sounds.

fatigue.

Detecting both types of fatigue simultaneously, incorporating context, and handling different groupings of sensors create a challenge in designing such a system. Data preparation

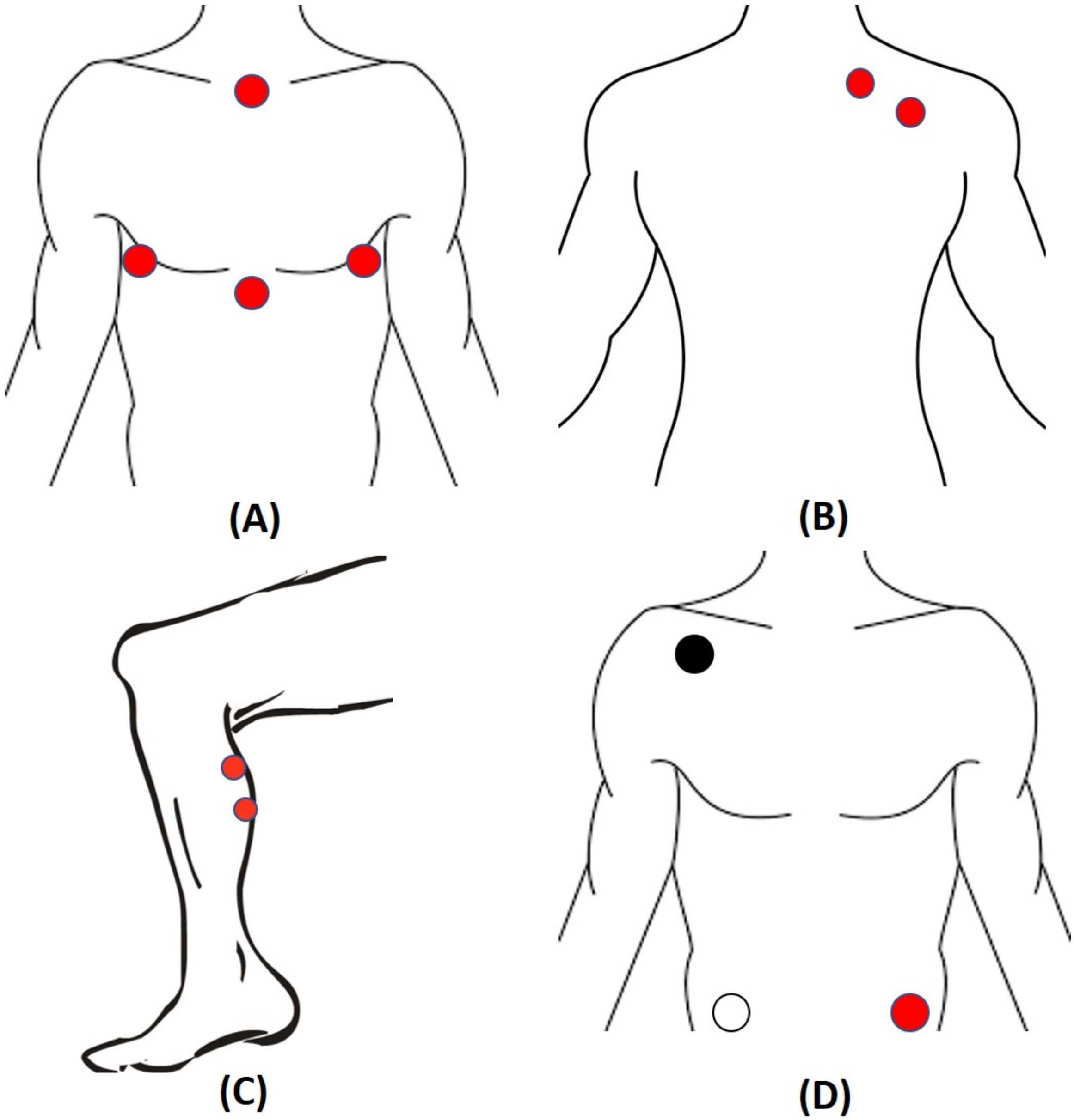


Figure 5.6: Sensor Placement (A) Breathing Sounds recorded from the suprasternal notch, xiphoid process, and on the left and right lung (B) EDA recorded from the shoulder, (C) EMG recorded from the leg, (D) ECG attached to the right shoulder, the left, and the right hip

and analysis become more complicated in this system. To meet this challenge, we employ *Dynamic Data Driven Application System* (DDDAS) paradigm [94]. DDDAS is an approach where the instrumentation and the computation model are dynamically managed

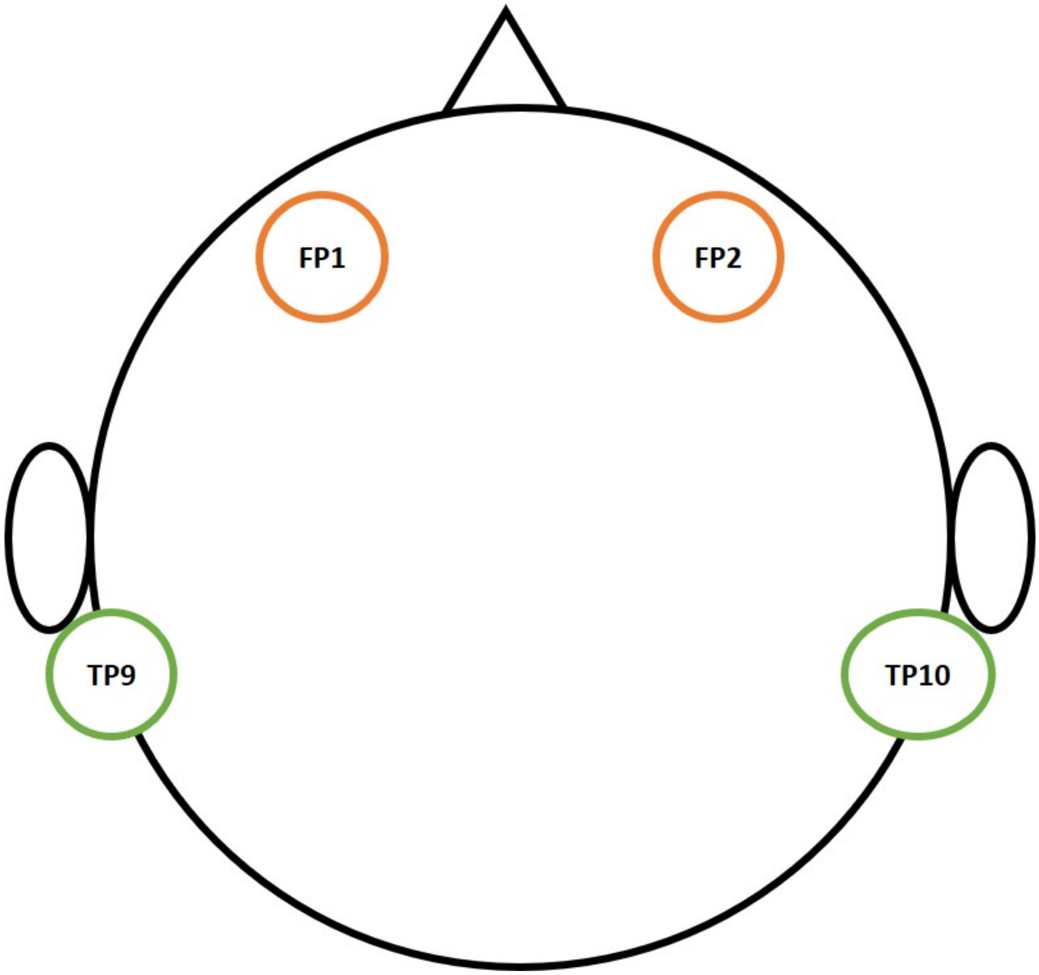


Figure 5.7: EEG sensor positions in the 10-10 electrode system used by MUSE. It records data from the TP9, FP1, FP2, and TP10 positions in the system.

in an application system. Therefore, this approach is perfectly suited to be used in this application. This paradigm will be used to handle data preparation and manage the detection of both types of fatigue. Figure 5.9 gives an overview of this method.

Some systems of the body may be affected by both types of fatigue, while others may be affected by just one of them. For example, EEG may not have enough information to detect physical fatigue as the brain is not directly impacted by it. Similarly, EMG may not have enough information to detect cognitive fatigue. Therefore, the data preparation to detect the two types of fatigue is different. This also dictates how the model to detect the two fatigue is made.

Knowing the context of the collected data helps at this stage. If the data was collected during a purely physical task, cognitive task, or a mix of both, it can be prepared accordingly and the appropriate model is chosen.

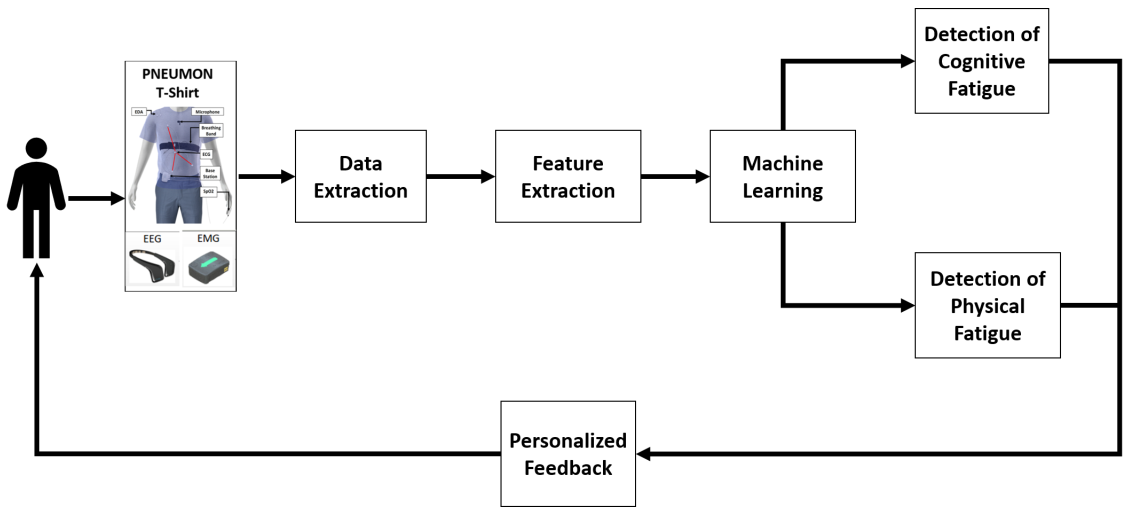


Figure 5.8: The KOPOS System Framework [93]. Data is extracted from the sensors embedded in the sensor suit. The extracted data is processed and features are extracted from them. Machine learning models are created from the extracted features. These models detect physical and cognitive fatigue. A feedback is provided to the user.

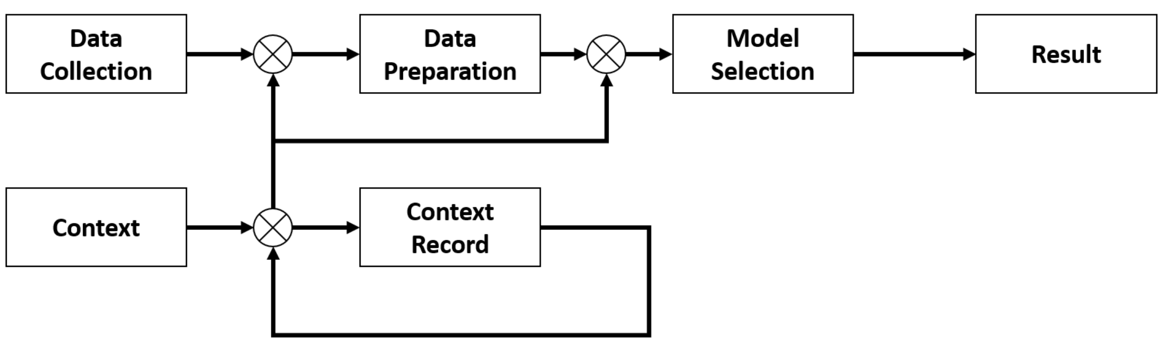


Figure 5.9: Context Integration in the KOPOS system [93]. Due to the complex nature of detecting physical and cognitive fatigue, two models are created. One detects physical fatigue, and the other detects cognitive fatigue. These two models accept data from different sets of sensors. Contextual information is used to select the models and prepare the data appropriately. If the data is recorded in a purely cognitive task, then the cognitive fatigue model is used. If it is recorded during a purely physical task, then the physical fatigue model is used. Both models are used if it is recorded in a task that requires both physical and cognitive effort.

5.4 Graphical User Interface

To assist in interacting with the designed system, a GUI was designed. This GUI is intended to be used by researchers, medical experts, and neuroscientists to conduct studies on fatigue. Therefore, the designed GUI must be simple and intuitive.

The GUI was designed in PyQT [95], a python wrapper for the QT framework developed by Riverbank Computing. To make the GUI simple, its functionality is categorized into different tabs. These categories depend on the task that the user performs. When the user starts up the GUI; they are greeted with a launch page (Figure 5.10). On this page, they can enter the subject number and the session number. This page also allows them to toggle the different graphs for the real-time data (Figure 5.11).

At the top of the window, different tabs are displayed. Apart from the splash page, the user can select the tab for the physical and the cognitive tasks. Two fatigue indicators are displayed at the bottom of the window. One indicates cognitive fatigue, and the other indicates physical fatigue.

When the user starts the cognitive task, the GUI launches another GUI that allows the user to play the N-Back game. The user will be first taken to a splash page (Figure 5.12) where they can enter the user information and select the game type. The game then begins where the letters are shown in the middle of a blank screen (Figure: 5.13). Once the game is over, the user is taken back to the launch page of the first GUI.

This chapter described the KOPOS system, through which physical and cognitive fatigue can be detected concurrently. Next, we need to build and test the system. The following chapter will explain the different data sets used for this purpose.

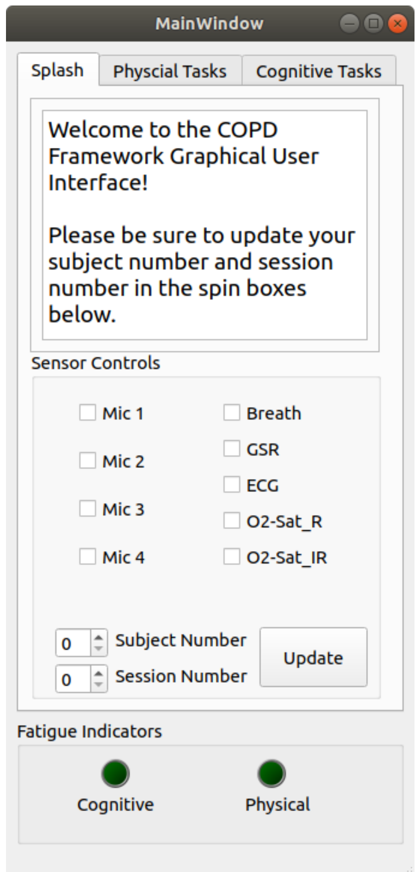


Figure 5.10: Graphical User Interface: Launch Page. Subject information can be entered on this page, along with selecting the sensors used (middle). Two indicators are provided, which light up when physical and cognitive fatigue is detected (bottom). Controls for the physical and cognitive tasks are hidden within different pages, which can be selected using the respective tabs (top).

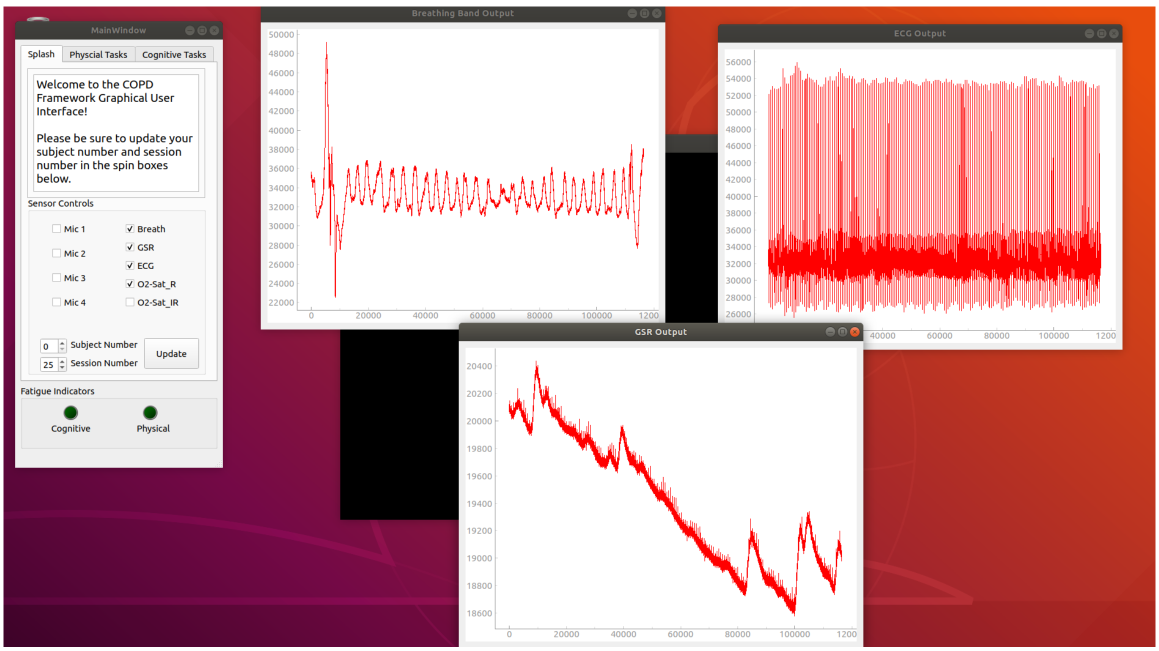


Figure 5.11: Graphical User Interface: Physical Tasks. Real-time graphs for each sensor open up in new windows. The subject's physiological state can be monitored through these graphs.

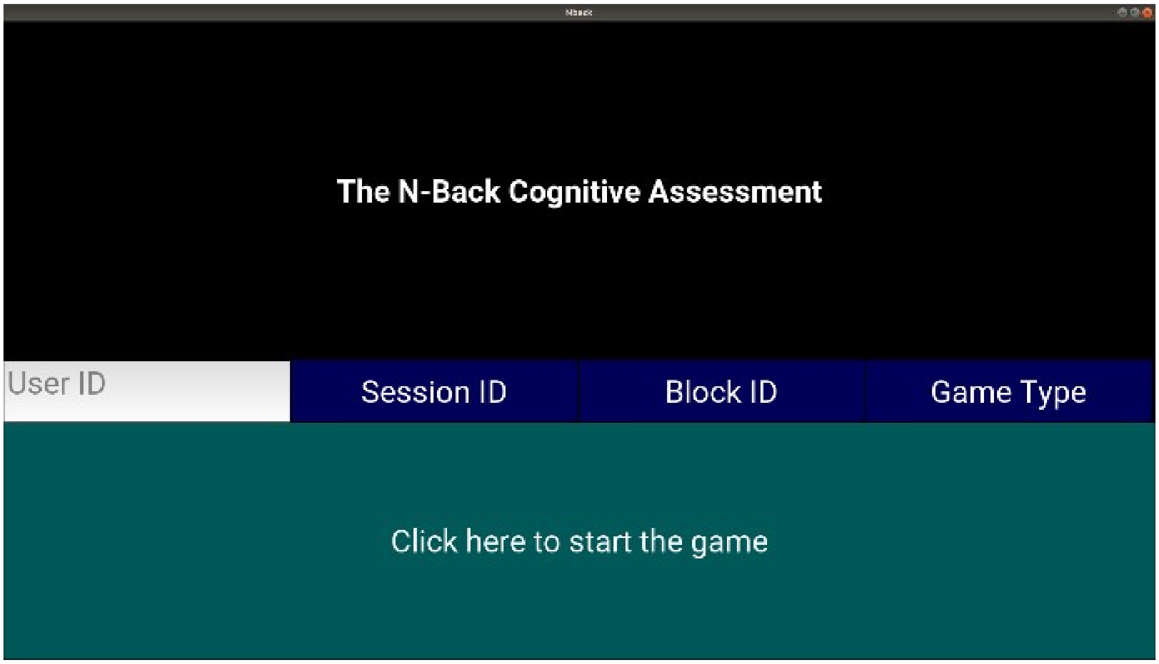


Figure 5.12: Graphical User Interface: Cognitive Task Splash Page. Subject information can be entered on this page (leftmost tab). Session information can also be entered here (middle two tabs). This page also provides the ability to select the game type (rightmost tab).

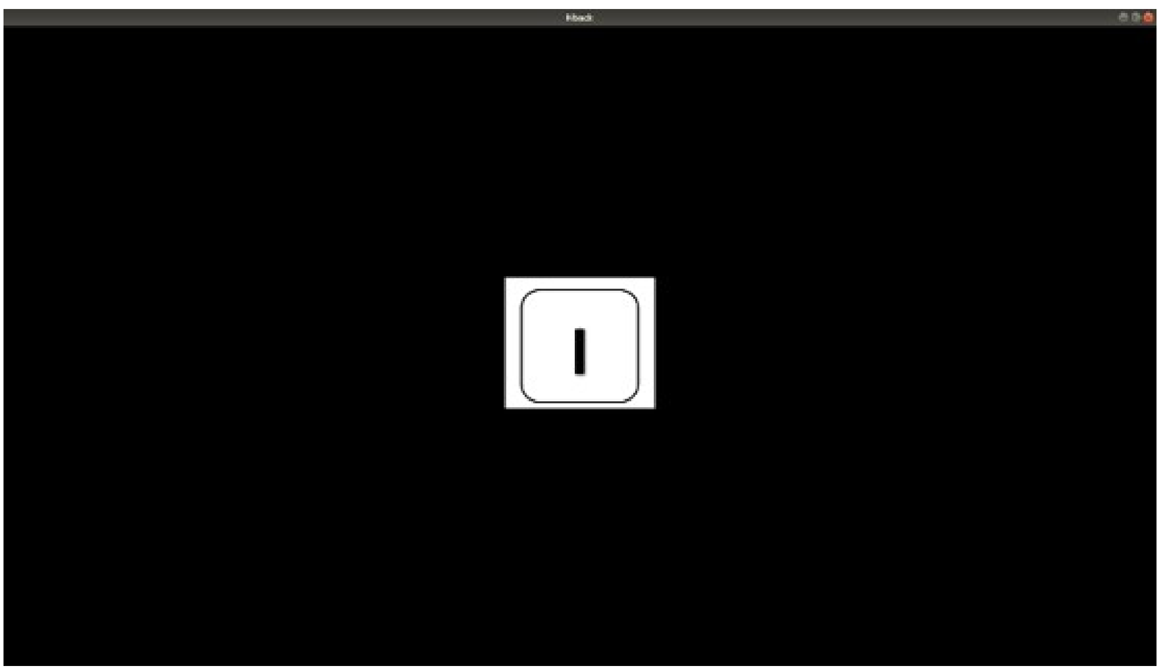


Figure 5.13: Graphical User Interface: Cognitive Task. This screen allows the subject to play the different tasks. Series of letters are displayed in the middle of the screen.

CHAPTER 6
MULTI-MODAL DATA SETS

This chapter details the different data sets used to build and validate the KOPOS system. It describes a study that was performed where both physical and cognitive fatigue was induced. Two studies where only one of the fatigue is induced are also described.

6.1 The KOPOS Data Set

A study was designed to build and validate the proposed KOPOS system. This study was conducted with ten healthy participants and had the necessary approval from the Institutional Review Board (IRB) of the University of Texas at Arlington (UTA).

Two conditions are necessary to build and validate the system data: low/no fatigue and fatigue. To collect this data, the designed study induces fatigue in the participants. During this time, physiological data are recorded from them using the KOPOS system. The study is designed to induce both physical and cognitive fatigue.

To induce physical fatigue, the participants are instructed to walk on a treadmill [93]. The following protocol is used.

- Walk at a speed of 1.7mph on a 10% incline for 3 minutes.
- Walk at a speed of 2.5mph on a 12% incline for 3 minutes.
- Stand for 1.5 minutes while post-task data is recorded.

To induce cognitive fatigue, the participants are asked to perform an N-Back task [34, 96, 97, 98]. In this task, the participant is shown a sequence of letters one after another. The participant must recognize if the current letter matches the letter presented N steps back. If it does, then the participant must perform the instructed action. In this study, two games were designed using the N-Back task; 0-Back, and 2-Back. The 0-Back game is a cognitively less demanding game. The subjects are given a target letter. They are then presented with the sequence of letters. If the current letter matches the target letter, the participant must press the designated button. This task is considered as the baseline task against which the other tasks are compared. The 2-Back game is a relatively more demanding game. The participants are presented with a series of letters. If the current letter matches the letter presented two steps back, the participant must press the designated button [93]. Figure 6.1 shows the N-Back task.

The study is conducted for two sessions. Each of these sessions is conducted on separate days. On one day, the participants perform the study in the morning and on the other day in the afternoon. This is done to remove the effect of fatigue experienced due to the activities of the day.

The study, which is conducted to validate the proposed framework, consists of five phases.

- After being fitted with the sensors, a baseline reading is recorded from the participants in the first phase. This baseline data will be used to normalize the signal parameters.

- In the second phase cognitively simple game, 0-Back, is played. The participant plays two rounds of the 0-Back game.

- In the third phase, the participants are asked to perform the physical task.

- Next, in the fourth phase, the participants are asked to play the cognitively challenging, 2-Back, game. They play six rounds of the 2-Back game in order to induce cognitive fatigue.

- Finally, in the fifth phase, the participants must play two rounds of the 0-Back game again.

The tasks in the study are the same for both sessions. The difference between the two sessions is the order of the tasks. Figures 6.2 and 6.3 illustrate the order of the tasks for both sessions. Session 1 follows the order described above. In the second session, the cognitively challenging 2-Back game is played before the physical task. This assures the negation of physical fatigue on cognitive fatigue and vice versa in the analysis.

Between each phase, the participants are asked to fill out a survey (Appendix C and D). This survey quantifies their subjective level of fatigue. It is also designed to gauge their subjective experience performing the task. The participants are also asked to fill out a survey at the beginning of the study. This survey is designed to get their baseline reading. This is used to normalize their responses.

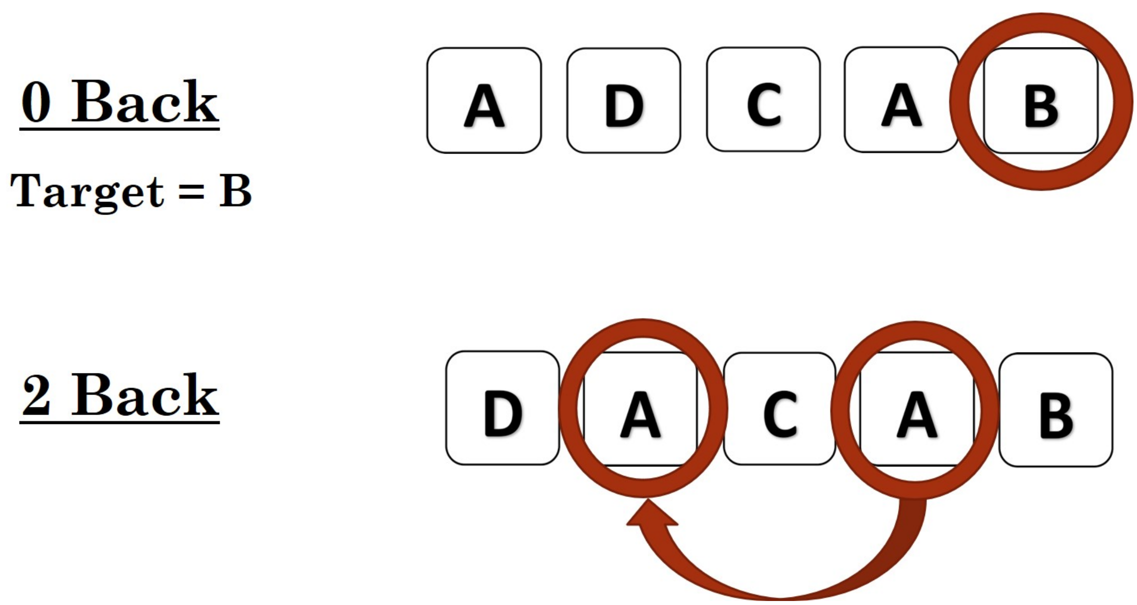


Figure 6.1: N-Back game (Top) 0-Back (Bottom) 2-Back. In the 0-Back game, the participant is given a target letter. They are then provided with letters in a sequence. If the current letter matches the target letter, they must press the space bar. In the 2-Back game, the participants are provided with letters in a sequence. If the current letter matches the letter given two steps back, they must press the space bar.

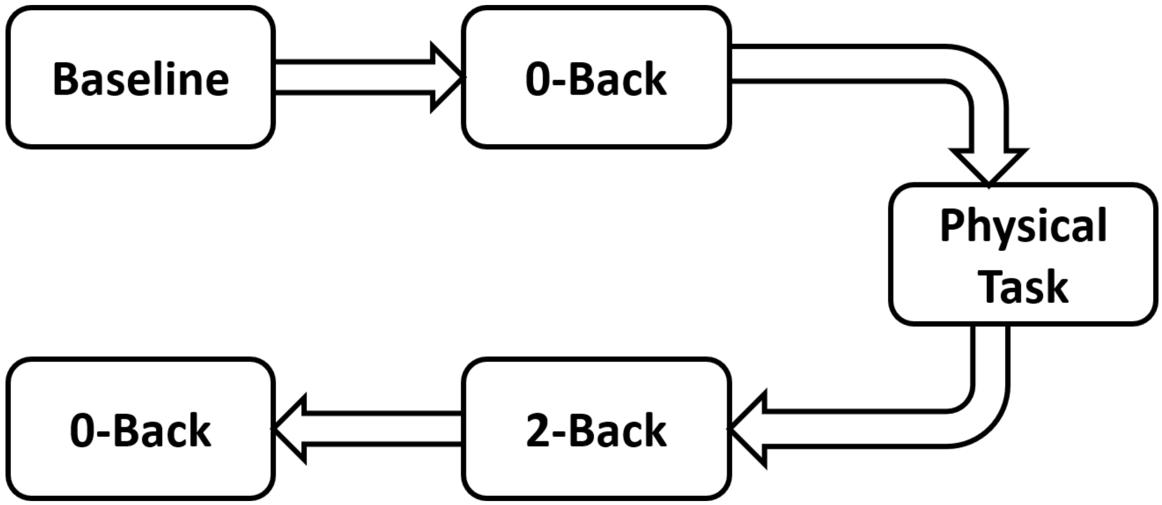


Figure 6.2: Protocol for Session 1 of the study to evaluate the KOPOS system. Baseline data is first extracted from the participants. They are then asked to play the 0-Back game. Next, they perform the physical task. They are then asked to play the 2-Back game. Finally, they play the 0-Back game again. This protocol is used to induce both physical and cognitive fatigue.

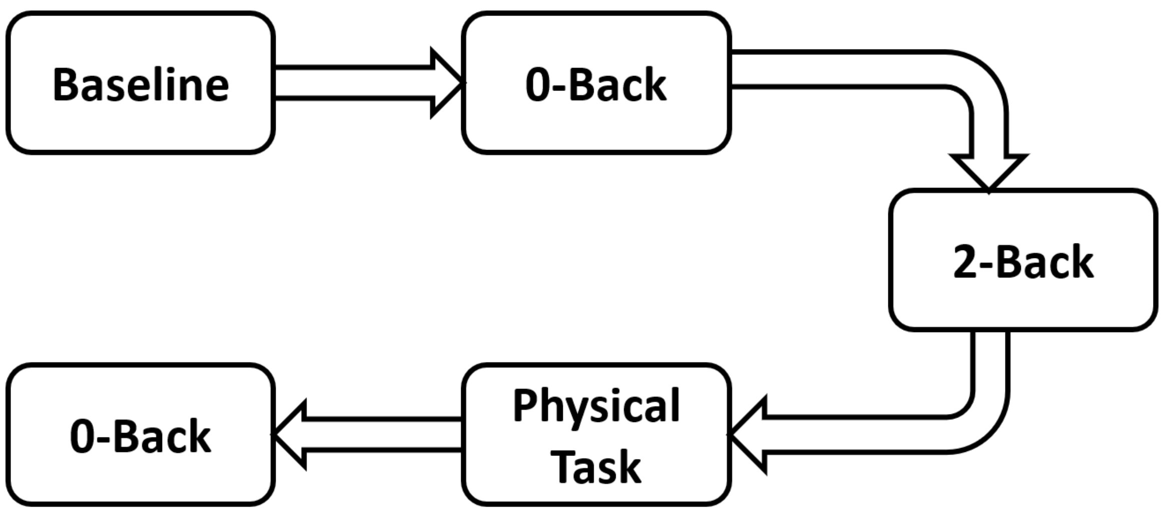


Figure 6.3: Protocol for Session 2 of the study to evaluate the KOPOS system. Baseline data is first extracted from the participants. They are then asked to play the 0-Back game. Next, they are asked to play the 2-Back game. After that, they perform the physical task. Finally, they play the 0-Back game again. This protocol is used to induce both physical and cognitive fatigue.

6.2 Cognitive Fatigue Data Set

In the previous study, the KOPOS system was built and validated on the data collected during a study specifically designed for the system. The study consisted of 10 participants during two sessions. To improve the system, a model was created using data from another study. This section discusses the data used to build the model for cognitive fatigue.

The data that was used was collected by a study conducted by Rajavenkatanarayanan *et al.* [99, 100] published at HRI 2020 conference. In this study, the authors worked on the human-robot interaction (HRI) paradigm, incorporating the human cognitive state. In a collaborative setup where robots and humans are working together to perform a task, safety is of the utmost importance. An essential factor of this safety is the human's capability to be aware of and avoid risks associated with working with a robot. Thus, during this time, the human must be alert and conscious of the work environment. By incorporating the cognitive state, the authors tried to make the HRI environment safer.

In this study, the authors looked at two aspects of human cognition, sleep quality and working memory. To assess the sleep quality, a Fitbit band was used. This band is a fitness monitor and an activity tracker that can be mounted on the wrist. Along with monitoring the activity, it can also record sleep data. The Fitbit band records the sleep data as the time spent in each sleep cycle. This data is also known as a hypnogram.

Thirty participants were recruited for the study. Of these, 23 were male, and 7 were female. Each participant was given the Fitbit band to wear continuously for five days. Sleep data was recorded during these days. The participants were asked to perform some cognitive tasks on two of the five days. These tasks were designed to assess their cognitive state. They were designed based on the N-Back task. Figure 6.5 illustrates the N-Back task that was designed.

The participants are first asked to attach the sensors to the body, and the baseline data are recorded. Next, they are asked to play a practice round of the 0-back task. This is done so that all subjects know how to perform the task beforehand. After this, the participants are asked to perform two rounds of the 0-Back task. After a break of a few minutes, the participants are asked to perform a practice round of the 2-Back task. Finally, the participants perform two rounds of the 2-Back task. Figure 6.4 illustrates the protocol employed.

While the participants performed the tasks, physiological data are extracted from them. ECG, EDA, and EEG are extracted from the participants. Analysis of this data would indicate the human cognitive state in the HRI application.

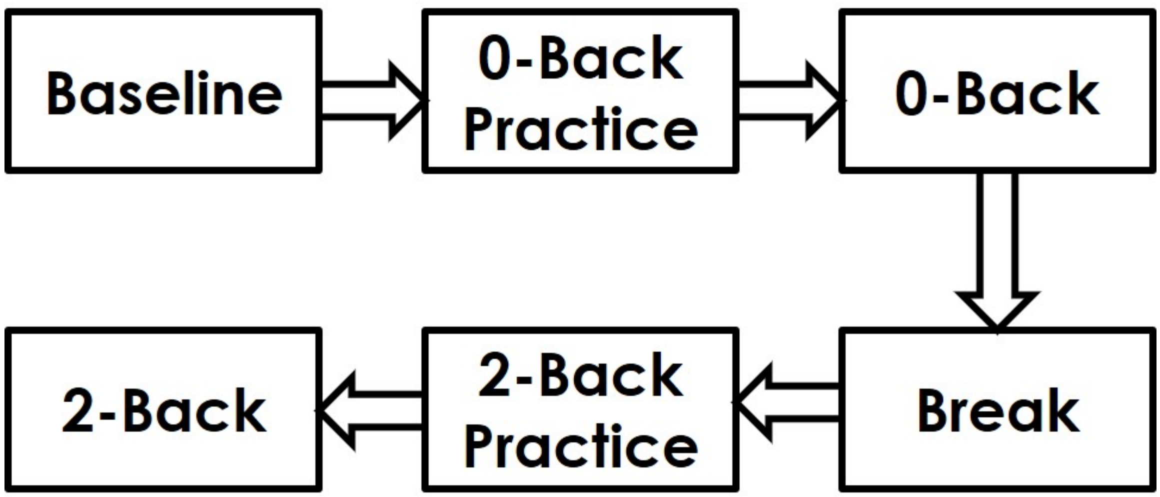


Figure 6.4: Study Protocol used in [99]. Baseline data is first extracted from the participants. They are then asked to perform a practice round of the 0-Back task, followed by two rounds of the 0-back task. After a break, they perform a practice round of the 2-Back task and then two rounds of the 2-Back task. This protocol was used to induce cognitive fatigue.

6.3 Physical Fatigue Data Set

As discussed before, the KOPOS study contains 10 participants. Therefore to create a more reliable model, another data set was used in conjunction with the KOPOS data set to build a model for physical fatigue.

The data set that was used was collected by a study conducted by Vollmer *et al.* [101].

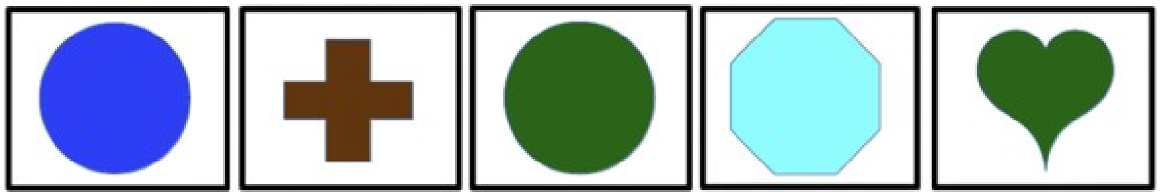


Figure 6.5: N-Back task used in [99]. The participants are presented with different shapes in a sequence. If the current shape matches the shape provided N steps back, the participants must press the space bar. Using this task, the authors were able to induce cognitive fatigue.

This data set is publicly available on PhysioNet [61]. The data set consisted of 13 healthy adult subjects where they were asked to perform different tasks. While the subjects performed these tasks, physiological data are extracted from them. ECG, photoplethysmography, accelerometry, oxygen saturation, respiration, heart rate, heart rate variability, and RR intervals are extracted from the subjects. These data record the different physiological changes in the body due to the different tasks.

The protocol of the study is shown in Figure 6.6. At the start of the study, the subjects were asked to attach the different sensors to their body. After this, five minutes of baseline data were recorded. This data was recorded while the subjects stood upright on a treadmill. The subjects were then instructed to walk on the treadmill for five minutes at a speed of 1.2 MPH. Next, the subjects were asked to perform a 2-Back task while standing still. Lastly, the subjects walked on the treadmill for five minutes at 1.2 MPH at 15% inclination.

This study was chosen as the method of inducing physical load is similar to the method in the KOPOS study.

This chapter introduced various data sets used to create and test the KOPOS system. The next chapter describes the analysis performed and the models built using the data set.

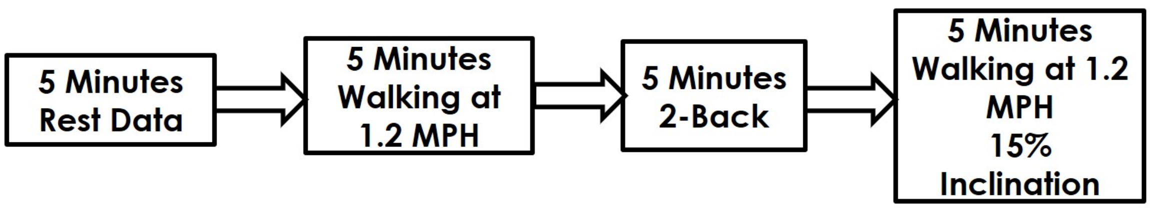


Figure 6.6: Protocol for Physical Fatigue from [101] [61]. Five minutes of Rest data is extracted from the participants. They are then asked to walk for five minutes at 1.2 MPH. Next, perform a 2-Back task for five minutes. Finally, they walk for five minutes on 15% inclination at 1.2 MPH. This protocol was used to induce physical fatigue.

CHAPTER 7

MULTI-MODAL DATA ANALYSIS AND THE KOPOS SYSTEM EVALUATION

This chapter discusses the analysis performed on the data collected from the studies detailed in the previous chapter. This chapter also talks about models created to detect physical and cognitive fatigue.

7.1 Cognitive Fatigue Detection

As explained in the previous chapter, two distinct data sets were considered. The first data set contains the data collected for the KOPOS study. The second data set contains the data collected from the study conducted by Rajavenkatanarayanan *et al.* [99]. Using these two data sets, two types of analysis were performed.

7.1.1 Analysis: The KOPOS data set

The KOPOS study was performed in five stages. More details are explained in Section 6.1. The data collected from this study was used to build a model to detect cognitive fatigue.

From this study, three stages were important to analyze cognitive fatigue. These were baseline, the First 0-Back game, and the 2-Back game. The data set consisted of multiple participants who may have biological differences. This means that the ‘normal’ condition for each participant may be different. Therefore, the absolute value of the physiological data would not help us identify the fatigue condition. To solve this issue, data from each stage is subtracted by the baseline data. This quantifies the change in the physiological state due to the induction of fatigue. Data from the 0-Back game represents the physiological state during low cognitive load. As explained before, the 2-Back game was played for six rounds. This was done to ensure that the fatigue was induced. From these rounds, the data from the fifth and the sixth round was considered to represent the physiological state during cognitive fatigue.

The first step in the analysis was to analyze the survey questions asked during the baseline and after each phase. To perform the analysis for cognitive fatigue, a comparison was made between Baseline, First 0-Back, 2-Back, and Second 0-Back. A Repeated Measure One-Way ANOVA (RANOVA) was performed on the survey data. RANOVA is an ANOVA test that uses a repeated measure design. A repeated measure design is similar to paired groups, as explained in Section 4.3. The groups of data set in a repeated measure design have a common link. For example, data is collected from subjects after giving Drug A, B, and C. Multiple comparisons were performed on the data to identify the pairs of significantly different stages.

Table 7.1 lists the questions asked in the survey. To simplify the tables, each question is associated with an identifying letter. In the following tables, the questions are referenced by the identifying letters. Table 7.2 and 7.3 presents the result from the RANOVA and the multiple comparison test. All questions except for Question F were performed between Baseline, First 0-Back, 2-Back, and Second 0-Back, question F was not relevant for the Baseline phase. The results show that the P values of the RANOVA test for all questions are less than 0.05. This indicates that the survey responses between the stages were significantly different for all questions. Moreover, from the multiple comparison test, it was observed that the questions about cognitive fatigue (Questions A, C, D, and F) were significantly different between First 0-Back and 2-Back. This shows that subjectively cognitive fatigue was induced in the subjects.

From the multimodal data collected, ECG, EDA, and EEG data were analyzed. The data were first preprocessed to remove any noise from the signal. This ensures that any analysis done is as close to the actual physiological values as possible. To process the ECG and EDA signals a package called Neurokit2 [102] was used. ECG data was first cleaned using a high pass Butterworth filter. In a high pass filter, all the frequency components from a signal below a cut-off frequency are removed. This ensures that the noise below the cut-off frequency is removed. In this filter, the cut-off frequency was 0.5 Hz. After this, a notch filter is applied to the signal. This filter removes frequency components from a single frequency. In this filter, the notch filter was designed to remove 50 Hz. The resulting signal is the clean ECG signal devoid of noise.

Like the ECG signal, the EDA signal was also filtered. This signal is first passed through a low pass Butterworth filter. In a low pass filter, all the frequency components above a cut-off frequency are removed. The filter was designed with a cut-off frequency of 3 Hz. EDA can be decomposed into two components, phasic and tonic [103]. The phasic component of the EDA signal is the faster changing elements of the signal. This usually indicates physiological changes due to a stimulus. The tonic component of the EDA signal is the background characteristic of the signal. In this analysis, the phasic component of the EDA signal was extracted.

EEG signal quantifies brain activity. The raw EEG signal can be decomposed into five different EEG bands [104]. These are Delta waves, Theta waves, Alpha waves, Beta waves, and Gamma waves. Delta waves occur in the frequency range of 0.5 to 4 Hz. This wave is present during deep sleep. Theta waves occur between 4 to 7 Hz. This wave is associated with drowsiness and early stages of sleep. Alpha waves occur between 8 to 12 Hz. This wave is associated with normal awake conditions. Beta waves occur between 13 to 30 Hz. They are associated with active thinking. Gamma waves occur between 30 to 80 Hz. They are associated with sensory perception integration.

After preprocessing the signals, features are extracted from them. These features quantify the signal and provide a numerical value for its property. From the ECG signal, time-domain features and frequency domain features were extracted. Apart from these, features related to the Heart Rate Variability (HRV) were also extracted. HRV is the changes in the time between two successive heartbeats [105]. The number of Skin Conductance Response (SCR) peaks and the amplitude of SCR peaks are recorded from the EDA signal. SCR is the increase in skin conductance which is usually in response to a stimulus. Figure 7.1

shows a typical SCR peak. From the EEG signal, time-domain features and frequency domain features were extracted. These features were extracted from each EEG sensor (refer to Section 5.2) and for all EEG waves, including the raw EEG data. A detailed list of the features is provided in Appendix A.

In total, there were 169 features extracted from all signals. Some of the features were affected due to the induction of cognitive fatigue, while others were not affected. To reduce the dimensionality of the features, Principal Component Analysis (PCA) was performed. PCA is a method to reduce the dimensionality of the feature set while retaining the information of the larger set [106]. These extracted features are used to create models that detect cognitive fatigue.

Five classification algorithms were considered to create the model to detect fatigue. These were Random Forrest (RF), Neural Networks (NN), SVM, KNN, Gradient Boosting (GB), and Histogram-based Gradient Boosting (HB). An RF classifier is an ensemble method of classification [107]. Here, multiple decision trees are created during the training phase. Instead of considering the result of a single tree as the final result, all the trees are considered. NN is inspired by the way that the brain works [108]. The NN model consists of multiple connected units which receive and process data. These units may be arranged in multiple layers where each layer receives input from the previous layer. In SVM classification, the data are mapped into a space [109]. This algorithm then tries to discriminate the data points into different classes. KNN classifies a data point based on its distance to other data points. GB is a meta learner that creates a model from multiple weak models [110]. It builds the models in stages, optimizing the loss from the previous weaker model. HB works on a similar mechanism as GB. HB is a variation of GB where instead of working on continuous data, the data is split into bins. This improves the processing speed of the algorithm. Apart from these algorithms, a meta-algorithm, bootstrap aggregating (bagging), was also employed. In this algorithm, multiple versions of the base algorithm are created, and the aggregate of the results is considered the final result [111]. Bagging was applied for NN, SVM, and KNN.

Each model was created using K-Fold cross-validation. Here the data is divided into K groups. From these groups, one is considered as the testing set; the rest is chosen for training. Multiple models are created where each group is chosen as the test set once. For this study, the K was chosen as 10. A randomized grid search was employed to optimize the hyperparameters of the models. To study the performance of the model, the F_1 score was calculated. F_1 score is the harmonic mean of precision and recall [112].

Table 7.4 summarizes the characteristics of the models developed to detect cognitive fatigue. The table below contains the F_1 score for all models. F_1 score ranges from 0 to 1. The higher the F_1 score, the better the performance of the model. The results show that KNN, SVM, and KNN + Bagging give the highest F_1 scores. In addition, models built using RF, GB, and HB can capture cognitive fatigue with high accuracy, so each of these models can be used in cognitive fatigue detection systems.

Table 7.1: Survey Questions. The participants were asked to fill out a survey after each phase. In the following tables, these questions will be referred to by the adjacent number.

	Survey Questions
A	How tired do you feel overall?
B	How physically tired do you feel?
C	Do you feel mentally fatigued?
D	Do you feel sleepy or drowsy?
E	Do you feel active and energetic?
F	How difficult was the task?

7.1.2 Analysis: The KOPOS data set + Original data set

As explained in Section 6.2, there was some limitation with the KOPOS study. The major limitation was that there were only ten subjects recruited for the study. This limitation reduces the power of the analysis performed. To mitigate this issue, data set from a study conducted by Rajavenkatanarayanan *et al.* [99] was used in conjunction with the KOPOS data to build and test the models to detect cognitive fatigue. This data set will be referred

Table 7.2: Cognitive Survey Analysis 1: RANOVA with Multiple Comparison. It can be observed that the questions related to cognitive fatigue (Questions A, C, and D) were significantly different between First 0-Back and 2-Back, indicating that cognitive fatigue was induced.

	A	B	C	D	E
RANOVA	<0.001*	<0.001*	<0.001*	<0.001*	<0.001*
Baseline V/S First 0-Back	1	1	0.623	0.199	1
Baseline V/S Second 0-Back	0.043*	1	0.015*	<0.001*	1
Baseline V/S 2-Back	0.009*	1	0.007*	<0.001*	1
First 0-Back V/S Second 0-Back	0.05*	0.648	0.009*	0.006*	0.406
First 0-Back V/S 2-Back	0.009*	1	0.005*	0.001*	0.668
Second 0-Back V/S 2-Back	0.843	1	1	1	1

* = P Value < 0.05

Table 7.3: Cognitive Survey Analysis 2: RANOVA with Multiple Comparison. It can be seen that there was a significant difference in the question regarding subjective difficulty between the First 0-Back and the 2-Back game.

	F
RANOVA	<0.001*
First 0-Back V/S Second 0-Back	1
First 0-Back V/S 2-Back	<0.001*
Second 0-Back V/S 2-Back	<0.001*

* = P Value < 0.05

Table 7.4: Cognitive Fatigue Model Performance. The table lists the F_1 Score for all models. It can be observed that KNN, SVM, and KNN + Bagging give the highest F_1 scores and therefore had the best performance indicating that these models can be used to detect cognitive fatigue.

Model	F_1 Score
RF	0.95
NN	0.67
KNN	0.96
SVM	0.96
NN + Bagging	0.48
KNN + Bagging	0.96
SVM + Bagging	0.41
GB	0.94
HB	0.94

to as the 'original data set' for the following analysis.

In the study, the authors collected multi-sensory data while the cognitive load was induced. They extracted ECG, EDA, and EEG signals from the participants. These signals

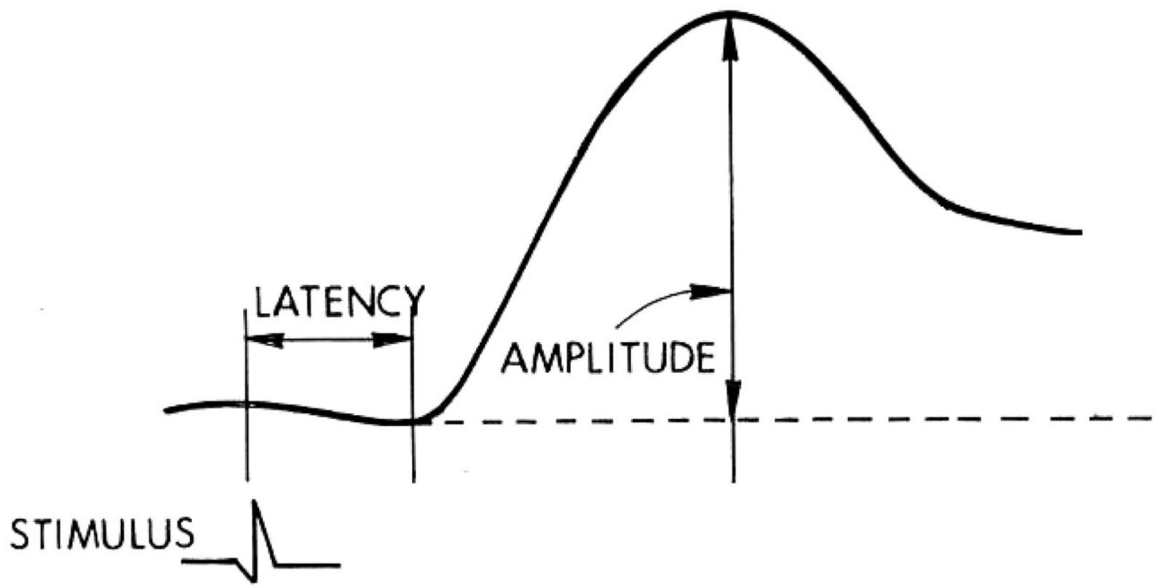


Figure 7.1: Skin Conductance Response in the EDA/GSR signal[113]. After a physiological/psychological stimulus, the EDA/GSR signal rises. There is a slight delay between the stimulus and the response. The analysis of this response helps us study the physiological effect of the stimulus.

were processed and quantified in the same way as explained in the previous section. This study was conducted in stages, as shown in Figure 6.4. From these stages, two were important to building the cognitive fatigue detection model. These were 0-Back and 2-Back. The models were created using the data from these two stages.

In the following analysis, the models were created using the original data set. The created model was then tested against the KOPOS data. This analysis helps answer two questions. The first question is whether a better model can be created using a larger data set. The second question is whether directly using a model created on a different data set can be used to detect cognitive fatigue for any application.

Table 7.5 lists the performance of the models created using the original data set. The table lists the F_1 score for the models when tested on the Original data set as well as when tested on the KOPOS data set. From the result, it can be seen that GB had the best performance when it was validated on the original data set. This model had a similar performance when tested on the KOPOS data set. Although the model's performance was promising, it was lower than the model created and tested on the KOPOS data set. Moreover, KNN and KNN + Bagging had an F_1 score of 0 when tested on the KOPOS data set. Their F_1 score with the Original data set was also low. This means that these algorithms were not efficient enough to detect cognitive fatigue. This result indicates that a model to detect cognitive fatigue will need to include data from the application in which the system is to be used. This means that the KOPOS system will need a calibration phase where labeled data are recorded and the models are reconfigured to adapt to the application.

Table 7.5: Cognitive Fatigue Model (KOPOS + Original) Accuracy. The table lists the F_1 for all models for both the Original Data Set as well as the KOPOS Data Set. It can be observed that GB had the highest F_1 score when validated on the KOPOS data set and therefore had the best performance.

Model	Original Data Set F_1	KOPOS Data Set F_1
RF	0.71	0.66
NN	0.73	0.56
KNN	0.61	0
SVM	0.73	0.50
NN + Bagging	0.61	0.29
KNN + Bagging	0.57	0
SVM + Bagging	0.62	0.33
GB	0.73	0.73
HB	0.67	0.64

7.2 Physical Fatigue Detection

As explained in the previous chapter, two data sets were considered to build a model to detect physical fatigue. The first data set was the KOPOS data set. The second data set was an online data set collected by Vollmer *et al.* [101].

7.2.1 Analysis: The KOPOS data set

The KOPOS study was performed in stages. Among the stages, two stages were important in analyzing physical fatigue. These were the Baseline and the Physical Task. Similar to the analysis for cognitive fatigue, the absolute physiological data was not considered while analyzing physical fatigue. Instead, the change in the physiological state due to the induction of fatigue was analyzed to detect fatigue. During the Physical Task stage, the participants were asked to walk on a treadmill. They were first asked to walk for three minutes at 1.7 MPH on a 10% incline. They were then asked to walk for three minutes at 2.5 MPH on a 12% incline. Finally, 1.5 minutes of post-task data were collected. From this task, the data from the first two minutes was considered as the low fatigue condition. At this point, the participants had just started the exercise and the physical load induced was low. The last two minutes of the stage were considered as the physical fatigue condition. Here a high physical load is induced on the participant. Moreover, the participant experiences a cumulative physical load due to the physical load experienced at the start of the exercise. The last two minutes of the stage contains data from both the higher load exercise as well as post-exercise.

From the multimodal data collected ECG, EDA, and Respiration signals were analyzed. ECG and EDA were preprocessed in a similar way as during the cognitive fatigue analysis. As explained in Section 5.3 EEG data was not relevant while analyzing physical fatigue. Thus this signal was not considered while building the model to detect physical fatigue. Respiration is one of the physiological processes which is impacted by physical load [114]. This signal is therefore used to detect physical fatigue. To preprocess the respiration signal, it is first filtered. This is done by passing the signal through a band-pass filter. In this filter, the signal is allowed to retain frequency components within a specified range. This ensures that the noise below and above the range is removed. A Butterworth band-pass filter was designed with allowable frequencies between 0.05 Hz and 3 Hz to preprocess the respiration signal.

After preprocessing the signals, features were extracted from them. The features extracted from the EDA signal were the same as the ones mentioned for cognitive fatigue as listed in Section 7.1.1. Time-domain and frequency domain features were extracted from the Respiration signal. For the ECG signal, apart from the features extracted discussed for the cognitive fatigue, respiration influenced features were also extracted. These features describe how the ECG is affected by respiration. A detailed list of features is provided in Appendix B.

In total, there were 74 features extracted from the signals. Like cognitive fatigue, some of these features were affected due to physical fatigue, while others were not. Therefore, the dimensionality of features was reduced using PCA. The algorithms used and the method to build the physical fatigue model were the same as those used to build the cognitive fatigue models.

Table 7.6 lists the performance of various models used to measure physical fatigue. The following table shows the F_1 score of all models. As mentioned in Section 7.1.1, the F_1 score ranges from 0 to 1. The higher the F_1 score, the better the performance of the model. The results show that RF and KNN have the highest F_1 score. Overall, the generated models show promising performance. This result shows that any of these models can be used to determine physical fatigue in a system.

Table 7.6: Physical Fatigue Model Accuracy. The table lists the F_1 Score for all models. It can be observed that RF and KNN had the highest F_1 scores and therefore performed the best, indicating that these models can be used to detect physical fatigue.

Model	F_1 Score
RF	0.83
NN	0.74
KNN	0.83
SVM	0.80
NN + Bagging	0.74
KNN + Bagging	0.68
SVM + Bagging	0.70
GB	0.78
HB	0.76

7.2.2 Analysis: The KOPOS data set + Online data set

The physical data set in the KOPOS study suffered from the same limitation as the cognitive data set. To mitigate the issue, an online data set collected by Vollmer *et al.* [101] was used in conjunction with the KOPOS data set to build and test the models to detect physical fatigue. This data set will be referred to as the 'online data set' for the following analysis.

In the study, the authors collected multiple physiological signals. Among them, ECG and Respiration signals were common between their data set and the KOPOS data set. Therefore, these were the only signals considered while building the models. The study had multiple stages. Amongst them, three stages were important to analyze physical fatigue. These were Rest Data, Walking at 1.2 MPH, and Walking on 15% inclination. Walking at 1.2 MPH was considered a low fatigue condition while Walking on 15% inclination was considered as a high fatigue condition.

Similar to the analysis done in Section 7.1.2, the models were built on the online data set. These models were then tested on the KOPOS data set. The questions asked during the cognitive fatigue analysis were asked during the physical fatigue analysis as well.

Table 7.7 lists the performance of the created models using the online data set. From the result, it can be seen that HB had the best performance that was consistent between the two data sets. Although the model's performance was promising, the difference between the score of the online data set and the KOPOS data set was significant. This was true for the other models as well. Therefore, a similar conclusion can be reached that the KOPOS system will need a calibration phase where labeled data are recorded, and the models are reconfigured to adapt to the application.

Table 7.7: Physical Fatigue Model (KOPOS + Online) Accuracy. The table lists the F_1 for all models for both the Online Data Set as well as the KOPOS Data Set. It can be observed that HB had the highest F_1 score when tested on the KOPOS data set and therefore performed the best.

Model	Online Data Set F_1	KOPOS Data Set F_1
RF	0.95	0.59
NN	0.95	0.68
KNN	0.90	0.08
SVM	0.93	0.09
NN + Bagging	0.83	0.58
KNN + Bagging	0.98	0.09
SVM + Bagging	0.90	0.09
GB	1	0.66
HB	0.95	0.71

CHAPTER 8
CONCLUDING REMARKS

This thesis focused on creating a system to detect physical and cognitive fatigue concurrently. The designed system is intended to be used by researchers, medical experts, and neuroscientists to study fatigue in humans. Traditionally, the two types of fatigue are studied independently. Few studies have looked into how these two types of fatigue affect the body when they occur concurrently. In the real world, many tasks require both physical and cognitive effort. Thus, in real-world tasks, these two types of fatigue may occur at the same time. Studying them individually may obscure the effect of fatigue on the body. It may also prevent us from studying the way that fatigue occurs in the real world. The system's main advantage is that it provides a platform to study and detect fatigue concurrently. This allows the researchers to simulate and observe the two types of fatigue in the same experimental setup.

This thesis first chronicles our efforts to build such a setup. It first discusses systems designed to quantify and analyze physiological data. Using this data we were able to detect and diagnose different physiological conditions and states. In this area, the thesis discusses a system, Apsen, that was designed to pre-screen for sleep apnea in a home environment. The thesis also discusses an evaluation performed on a low-cost EMG sensor as an input modality for VR application using gesture recognition.

Next, the thesis documents our efforts to analyze and detect the two types of fatigue. First, it discusses our system to detect physical fatigue. It discusses an adaptive robotic system that was designed for upper arm rehabilitation. The designed system would challenge the user to perform the rehabilitation exercises, but also understand when the user needs help and provide that help. To understand when the user needs help, the system detects muscular fatigue by analyzing the EMG signal from the major muscle responsible for the movement. The thesis also discusses our project to study the two types of fatigue together. To this end, two systems were designed. In both systems, the participant would exert physical effort to play a cognitive game. The participant would use a robotic arm, configured in a joystick-like position, to play the game. Two games were designed, 'FROX' and 'Escape the Knight'.

8.1 The KOPOS System

At this point, with the lessons learned through the previous systems, we designed a system that was dubbed the KOPOS system. This system used a multi-sensory approach to detect and analyze the two types of fatigue. The system consisted of ECG, EMG, EEG, EDA, SpO_2, respiration, and breathing sounds.

One major challenge to create such a system is how the two types of fatigue affect the body. Some of the body's subsystems that the two types of fatigue effect are the same, while the others are different. To solve this issue, the DDDAS paradigm was employed. This allowed the integration of the context in which the data is recorded to analyze and detect the two types of fatigue.

8.2 Creation of the Models

A study was conducted to gather data in order to build the two fatigue detection models. This study was designed to induce both physical and cognitive fatigue in the participants. The collected data were processed and analyzed. Multiple machine learning models were evaluated using the data. The results showed that few of the models performed very well in detecting the two types of fatigue.

There was a limitation to the study performed. The study had only 10 participants. Due to this, the efficiency of the models created would be low. Other data sets were considered in conjunction with the study to build the fatigue detection models to solve this issue. From the result, it was found that, although the performance of the models was promising, it was lower than the models created using the study data set.

8.3 Final Thoughts

In this thesis, a system was created that can be used by researchers, doctors, and therapists to detect and study the two different types of fatigue. The designed system was simple and intuitive. This will allow people who may or may not have the technical experience to use the system. The thesis also presented a sensor suit that the user can use to attach the sensors easily. The analysis of the system showed promising results. Although, the performance of the system when built on another data set was lower than the one built on the study data set. This indicates that the system will need to be calibrated the user's study design before using the system. Overall, the designed system provides a platform to study an important phenomenon in humans, fatigue.

Appendices

APPENDIX A

COGNITIVE FATIGUE FEATURES

Table A.1: Features extracted for Cognitive Fatigue from ECG, EDA, and respiration signal [102]

Feature	Feature Name
HR	Mean Heart Rate
HRV_RMSSD	Square root of the mean of the sum of successive differences between adjacent RR intervals
HRV_MeanNN	Mean of RR intervals
HRV_SDNN	The standard deviation of the RR intervals
HRV_SDSD	The standard deviation of the successive differences between RR intervals
HRV_CVNN	The standard deviation of the RR intervals divided by the mean of the RR intervals
HRV_CVSD	The root mean square of the sum of successive differences divided by the mean of the RR intervals
HRV_MedianNN	The median of the absolute values of the successive differences between RR intervals.
HRV_MadNN	The median absolute deviation of the RR intervals.

HRV_MCVNN	The median absolute deviation of the RR intervals divided by the median of the absolute differences of their successive differences
HRV_IQRNN	The interquartile range (IQR) of the RR intervals.
HRV_pNN50	The proportion of RR intervals greater than 50ms, out of the total number of RR intervals.
HRV_pNN20	The proportion of RR intervals greater than 20ms, out of the total number of RR intervals.
HRV_VLF	Upper and lower limit of the very-low frequency band.
HRV_LF	Upper and lower limit of the low frequency band
HRV_LFHF	The ratio of low frequency power to high frequency power.
HRV_LFn	The normalized low frequency
HRV_HFn	The normalized high frequency,
HRV_LnHF	The log transformed HF.
HRV_SD1	Measure of the spread of RR intervals on the Poincaré plot perpendicular to the line of identity.
HRV_SD2	Measure of the spread of RR intervals on the Poincaré plot along the line of identity.
HRV_SD1SD2	The ratio between short and long term fluctuations of the RR intervals
HRV_S	Area of ellipse described by SD1 and SD2
HRV_CSI	The Cardiac Sympathetic Index

HRV_CVI	The Cardiac Vagal Index
HRV_CSI_Modified	The modified CSI
HRV_PIP	Percentage of inflection points of the RR intervals series
HRV_IALS	Inverse of the average length of the acceleration/deceleration segments.
HRV_PSS	Percentage of short segments.
HRV_PAS	Percentage of NN intervals in alternation segments.
HRV_GI	Guzik's Index
HRV_SI	Slope Index
HRV_AI	Area Index
HRV_PI	Porta's Index
HRV_C1d	The contributions of heart rate decelerations
HRV_C1a	The contributions of heart rate accelerations
HRV_SD1d	Long-term variance of contributions of decelerations
HRV_SD1a	Long-term variance of contributions of accelerations
HRV_C2d	The contributions of heart rate decelerations to long-term HRV
HRV_C2a	The contributions of heart rate accelerations to long-term HRV
HRV_SD2d	Long-term variance of contributions of decelerations
HRV_SD2a	Long-term variance of contributions of accelerations

HRV_Cd	Total contributions of heart rate decelerations to HRV.
HRV_Ca	Total contributions of heart rate accelerations to HRV.
HRV_SDNNd	Total variance of contributions of decelerations
HRV_ApEn	The approximate entropy measure of HRV
HRV_SampEn	The sample entropy measure of HRV
SCR_Peaks_N	The number of occurrences of Skin Conductance Response
SCR_Peaks_Amplitude_Mean	The mean amplitude of the SCR peak occurrences.
EEG_Mean	Mean of the EEG wave
EEG_STD	Standard Deviation of the EEG wave
EEG_Max	Maximum value of the EEG wave
EEG_Min	Minimum Value of the EEG wave
EEG_Centroid	Spectral Centroid of the EEG wave
EEG_Rolloff	Spectral Rolloff of the EEG wave

Table A.2: All EEG Features extracted for Cognitive Fatigue

Sensor Number	EEG Wave	Feature
	Raw EEG	EEG_Mean
		EEG_STD
		EEG_Max
		EEG_Min
		EEG_Centroid

		EEG_Rolloff
	Alpha	EEG_Mean
		EEG_STD
		EEG_Max
		EEG_Min
		EEG_Centroid
		EEG_Rolloff
	Beta	EEG_Mean
		EEG_STD
		EEG_Max
		EEG_Min
		EEG_Centroid
		EEG_Rolloff
	Gamma	EEG_Mean
		EEG_STD
		EEG_Max
		EEG_Min
		EEG_Centroid
		EEG_Rolloff
	Delta	EEG_Mean
		EEG_STD
		EEG_Max
		EEG_Min
		EEG_Centroid
		EEG_Rolloff
	Theta	EEG_Mean
		EEG_STD

		EEG_Max
		EEG_Min
		EEG_Centroid
		EEG_Rolloff
2	Raw EEG	EEG_Mean
		EEG_STD
		EEG_Max
		EEG_Min
		EEG_Centroid
		EEG_Rolloff
	Alpha	EEG_Mean
		EEG_STD
		EEG_Max
		EEG_Min
		EEG_Centroid
		EEG_Rolloff
	Beta	EEG_Mean
		EEG_STD
		EEG_Max
		EEG_Min
		EEG_Centroid
		EEG_Rolloff
	Gamma	EEG_Mean
		EEG_STD
		EEG_Max
		EEG_Min
		EEG_Centroid

		EEG_Rolloff
	Delta	EEG_Mean
		EEG_STD
		EEG_Max
		EEG_Min
		EEG_Centroid
		EEG_Rolloff
	Theta	EEG_Mean
		EEG_STD
		EEG_Max
		EEG_Min
		EEG_Centroid
		EEG_Rolloff
	Raw EEG	EEG_Mean
		EEG_STD
		EEG_Max
		EEG_Min
		EEG_Centroid
		EEG_Rolloff
	Alpha	EEG_Mean
		EEG_STD
		EEG_Max
		EEG_Min
		EEG_Centroid
		EEG_Rolloff
	Beta	EEG_Mean
		EEG_STD

		EEG_Max
		EEG_Min
		EEG_Centroid
		EEG_Rolloff
	Gamma	EEG_Mean
		EEG_STD
		EEG_Max
		EEG_Min
		EEG_Centroid
		EEG_Rolloff
	Delta	EEG_Mean
		EEG_STD
		EEG_Max
		EEG_Min
		EEG_Centroid
		EEG_Rolloff
	Theta	EEG_Mean
		EEG_STD
		EEG_Max
		EEG_Min
		EEG_Centroid
		EEG_Rolloff
	Raw EEG	EEG_Mean
		EEG_STD
		EEG_Max
		EEG_Min
		EEG_Centroid

		EEG_Rolloff
	Alpha	EEG_Mean
		EEG_STD
		EEG_Max
		EEG_Min
		EEG_Centroid
		EEG_Rolloff
	Beta	EEG_Mean
		EEG_STD
		EEG_Max
		EEG_Min
		EEG_Centroid
		EEG_Rolloff
	Gamma	EEG_Mean
		EEG_STD
		EEG_Max
		EEG_Min
		EEG_Centroid
		EEG_Rolloff
	Delta	EEG_Mean
		EEG_STD
		EEG_Max
		EEG_Min
		EEG_Centroid
		EEG_Rolloff
	Theta	EEG_Mean
		EEG_STD

		EEG_Max
		EEG_Min
		EEG_Centroid
		EEG_Rolloff

APPENDIX B

PHYSICAL FATIGUE FEATURES

Table B.1: Features extracted for Physical Fatigue from ECG, EDA, and respiration signal [102]

Feature	Feature Name
HR	Mean Heart Rate
HRV_RMSSD	Square root of the mean of the sum of successive differences between adjacent RR intervals
HRV_MeanNN	Mean of RR intervals
HRV_SDNN	The standard deviation of the RR intervals
HRV_SDSD	The standard deviation of the successive differences between RR intervals
HRV_CVNN	The standard deviation of the RR intervals divided by the mean of the RR intervals
HRV_CVSD	The root mean square of the sum of successive differences divided by the mean of the RR intervals
HRV_MedianNN	The median of the absolute values of the successive differences between RR intervals.
HRV_MadNN	The median absolute deviation of the RR intervals.

HRV_MCVNN	The median absolute deviation of the RR intervals divided by the median of the absolute differences of their successive differences
HRV_IQRNN	The interquartile range (IQR) of the RR intervals.
HRV_pNN50	The proportion of RR intervals greater than 50ms, out of the total number of RR intervals.
HRV_pNN20	The proportion of RR intervals greater than 20ms, out of the total number of RR intervals.
HRV_VLF	Upper and lower limit of the very-low frequency band.
HRV_LF	Upper and lower limit of the low frequency band
HRV_LFHF	The ratio of low frequency power to high frequency power.
HRV_LFn	The normalized low frequency
HRV_HFn	The normalized high frequency,
HRV_LnHF	The log transformed HF.
HRV_SD1	Measure of the spread of RR intervals on the Poincaré plot perpendicular to the line of identity.
HRV_SD2	Measure of the spread of RR intervals on the Poincaré plot along the line of identity.
HRV_SD1SD2	The ratio between short and long term fluctuations of the RR intervals
HRV_S	Area of ellipse described by SD1 and SD2
HRV_CSI	The Cardiac Sympathetic Index

HRV_CVI	The Cardiac Vagal Index
HRV_CSI_Modified	The modified CSI
HRV_PIP	Percentage of inflection points of the RR intervals series
HRV_IALS	Inverse of the average length of the acceleration/deceleration segments.
HRV_PSS	Percentage of short segments.
HRV_PAS	Percentage of NN intervals in alternation segments.
HRV_GI	Guzik's Index
HRV_SI	Slope Index
HRV_AI	Area Index
HRV_PI	Porta's Index
HRV_C1d	The contributions of heart rate decelerations
HRV_C1a	The contributions of heart rate accelerations
HRV_SD1d	Long-term variance of contributions of decelerations
HRV_SD1a	Long-term variance of contributions of accelerations
HRV_C2d	The contributions of heart rate decelerations to long-term HRV
HRV_C2a	The contributions of heart rate accelerations to long-term HRV
HRV_SD2d	Long-term variance of contributions of decelerations
HRV_SD2a	Long-term variance of contributions of accelerations

HRV_Cd	Total contributions of heart rate decelerations to HRV.
HRV_Ca	Total contributions of heart rate accelerations to HRV.
HRV_SDNNd	Total variance of contributions of decelerations
HRV_SDNNa	Total variance of contributions of accelerations
HRV_ApEn	The approximate entropy measure of HRV
HRV_SampEn	The sample entropy measure of HRV
RSP_Rate_Mean	The mean respiratory rate
RSP_Amplitude_Mean	The mean respiratory amplitude
RRV_RMSSD	The root mean square of successive differences of the breath-to-breath intervals
RRV_MeanBB	Mean breath-breath intervals
RRV_SDBB	The standard deviation of the breath-to-breath intervals
RRV_SDSD	The standard deviation of the successive differences between adjacent breath-to-breath intervals
RRV_CVBB	The standard deviation of the BB intervals divided by the mean of the BB intervals
RRV_CVSD	The root mean square of the sum of successive differences divided by the mean of the BB intervals
RRV_MedianBB	Median breath-breath intervals

RRV_VLF	Spectral power density pertaining to very low frequency band
RRV_LFn	The normalized low frequency
RRV_HFn	The normalized high frequency
RRV_SD1	Measure of the spread of breath-to-breath intervals on the Poincaré plot perpendicular to the line of identity
RRV_SD2	Measure of the spread of breath-to-breath intervals on the Poincaré plot along the line of identity.
RRV_ApEn	The approximate entropy of RRV
RRV_SampEn	The sample entropy of RRV
SCR_Peaks_N	The number of occurrences of Skin Conductance Response
SCR_Peaks_Amplitude_Mean	The mean amplitude of the SCR peak occurrences.
RSA_P2T_Mean	The mean of Respiratory Sinus Arrhythmia (RSA) peak-to-trough across all breath cycles in ms
RSA_P2T_Mean_log	The logarithm of the mean of RSA estimates.
RSA_P2T_SD	The standard deviation of all RSA estimates.
RSA_P2T_NoRSA	The number of breath cycles from which RSA could not be calculated.
RSA_PorgesBohrer	The Porges-Bohrer estimate of RSA
RSA_Gates_Mean	The mean of Respiratory Sinus Arrhythmia (RSA)

RSA_Gates_Mean_log	The log of the mean of Respiratory Sinus Arrhythmia (RSA)
RSA_Gates_SD	The Standard Deviation of the mean of Respiratory Sinus Arrhythmia (RSA)

APPENDIX C

SESSION 1 SURVEY

COPD Study

* Required

1. Subject Number *

____

2. Age *

____

3. Sex *

   Mark only one oval.

   ◯ Female
   ◯ Male
   ◯ Prefer not to say
   ◯ Other: _______________

4. Height *

____

5. Weight *

   in lbs

____

6. *

Inclusion Criteria:

- Subjects must be 18 - 64 years
- Follow all UTA rules (e.g. prohibited tobacco consumption on campus).
- Accept to follow the experimental procedure. For example, to be considered in the study, the participants must accept to wear the EEG, ECG, and the GSR sensors and agree to perform the exercises. Otherwise, they have the right to withdraw from the experiment at any time without consequences.
- Must be healthy without any kind of respiratory or cardiac illness.
- Must be physically able to run for 6 minutes on the treadmill continuously.

Exclusion Criteria:

- They should not be 65 years or older.
- The subjects should not have any physical injury that restricts their range of motion or their ability to perform the exercise.
- They should not have any known reasoning or physical disabilities.
- People with a silver allergy, with damaged/irritated skin, or people who have implanted devices of any kind (i.e. pacemakers, electronic infusion pumps) cannot participate in the study.
- They should not have any neurological disorder
- They should not have any respiratory or cardiac illness.
- They should not be immunocompromised.
- They should not be obese (a Body Mass Index (BMI) of 40 or higher).
- They should not have diabetes, kidney, or liver disease.

Mark only one oval.

- [ ] Accept
- [ ] Reject

Baseline

DIRECTIONS: You are asked to choose a number on each of the following questions to indicate how you are feeling, RIGHT NOW.
For example, if you have not eaten since yesterday, in response to the question, how hungry are you, you might want respond extremely hungry. You might want to respond by choosing a number close to 10, as shown below:

7. How tired do you feel overall? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all tired	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely tired

8. How physically fatigued do you feel? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all fatigued	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely fatigued

9. Do you feel mentally fatigued? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all fatigued	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely fatigued

10. Do you feel sleepy or drowsy? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all sleepy or drowsy	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely sleepy or drowsy

11. Do you feel active and energetic? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all active	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely active

12. Do you have difficulty breathing right now? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	A lot

Post Task 1 (0-Back)

DIRECTIONS: You are asked to choose a number on each of the following questions to indicate how you are feeling, RIGHT NOW.
For example, if you have not eaten since yesterday, in response to the question, how hungry are you, you might want respond extremely hungry. You might want to respond by choosing a number close to 10, as shown below:

13. How tired do you feel overall? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all tired	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely tired

14. How physically fatigued do you feel? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all fatigued	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely fatigued

15. Do you feel mentally fatigued? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all fatigued	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely fatigued

16. Do you feel sleepy or drowsy? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all sleepy or drowsy	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely sleepy or drowsy

17. Do you feel active and energetic? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all active	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely active

18. How difficult was the task? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Very Easy											Very difficult

Post Task 2 (Physical)

DIRECTIONS: You are asked to choose a number on each of the following questions to indicate how you are feeling, RIGHT NOW.
For example, if you have not eaten since yesterday, in response to the question, how hungry are you, you might want respond extremely hungry. You might want to respond by choosing a number close to 10, as shown below:

19. How tired do you feel overall? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all tired											Extremely tired

20. How physically fatigued do you feel? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all fatigued											Extremely fatigued

21. Do you feel mentally fatigued? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all fatigued											Extremely fatigued

22. Do you feel sleepy or drowsy? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all sleepy or drowsy											Extremely sleepy or drowsy

23. Do you feel active and energetic? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all active	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely active

24. Do you have difficulty breathing right now? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	A lot

25. How difficult was the task? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Very Easy	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Very difficult

Post Task 3 (2-Back)

DIRECTIONS: You are asked to choose a number on each of the following questions to indicate how you are feeling, RIGHT NOW.
For example, if you have not eaten since yesterday, in response to the question, how hungry are you, you might want respond extremely hungry. You might want to respond by choosing a number close to 10, as shown below:

26. How tired do you feel overall? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all tired	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely tired

27. How physically fatigued do you feel? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all fatigued	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely fatigued

28. Do you feel mentally fatigued? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all fatigued	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely fatigued

29. Do you feel sleepy or drowsy? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all sleepy or drowsy	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely sleepy or drowsy

30. Do you feel active and energetic? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all active	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely active

31. How difficult was the task? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Very Easy	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Very difficult

Post Task 4 (0-Back)

DIRECTIONS: You are asked to choose a number on each of the following questions to indicate how you are feeling, RIGHT NOW.
For example, if you have not eaten since yesterday, in response to the question, how hungry are you, you might want respond extremely hungry. You might want to respond by choosing a number close to 10, as shown below:

32. How tired do you feel overall? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all tired	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely tired

33. How physically fatigued do you feel? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all fatigued											Extremely fatigued

34. Do you feel mentally fatigued? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all fatigued											Extremely fatigued

35. Do you feel sleepy or drowsy? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all sleepy or drowsy											Extremely sleepy or drowsy

36. Do you feel active and energetic? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all active											Extremely active

37. How difficult was the task? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Very Easy											Very difficult

APPENDIX D

SESSION 2 SURVEY

COPD Study Session 2

* Required

1. Subject Number *

2. Age *

3. Sex *

   Mark only one oval.

   - Female
   - Male
   - Prefer not to say
   - Other: ____________

4. Height *

5. Weight *

   in lbs

6. *

Inclusion Criteria:

- Subjects must be 18 - 64 years
- Follow all UTA rules (e.g. prohibited tobacco consumption on campus).
- Accept to follow the experimental procedure. For example, to be considered in the study, the participants must accept to wear the EEG, ECG, and the GSR sensors and agree to perform the exercises. Otherwise, they have the right to withdraw from the experiment at any time without consequences.
- Must be healthy without any kind of respiratory or cardiac illness.
- Must be physically able to run for 6 minutes on the treadmill continuously.

Exclusion Criteria:

- They should not be 65 years or older.
- The subjects should not have any physical injury that restricts their range of motion or their ability to perform the exercise.
- They should not have any known reasoning or physical disabilities.
- People with a silver allergy, with damaged/irritated skin, or people who have implanted devices of any kind (i.e. pacemakers, electronic infusion pumps) cannot participate in the study.
- They should not have any neurological disorder
- They should not have any respiratory or cardiac illness.
- They should not be immunocompromised.
- They should not be obese (a Body Mass Index (BMI) of 40 or higher).
- They should not have diabetes, kidney, or liver disease.

Mark only one oval.

- Accept
- Reject

Baseline

DIRECTIONS: You are asked to choose a number on each of the following questions to indicate how you are feeling, RIGHT NOW.
For example, if you have not eaten since yesterday, in response to the question, how hungry are you, you might want respond extremely hungry. You might want to respond by choosing a number close to 10, as shown below:

7. How tired do you feel overall? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all tired											Extremely tired

8. How physically fatigued do you feel? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all fatigued											Extremely fatigued

9. Do you feel mentally fatigued? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all fatigued											Extremely fatigued

10. Do you feel sleepy or drowsy? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all sleepy or drowsy											Extremely sleepy or drowsy

11. Do you feel active and energetic? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all active											Extremely active

12. Do you have difficulty breathing right now? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all											A lot

Post Task 1 (0-Back)

DIRECTIONS: You are asked to choose a number on each of the following questions to indicate how you are feeling, RIGHT NOW.
For example, if you have not eaten since yesterday, in response to the question, how hungry are you, you might want respond extremely hungry. You might want to respond by choosing a number close to 10, as shown below:

13. How tired do you feel overall? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all tired	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely tired

14. How physically fatigued do you feel? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all fatigued	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely fatigued

15. Do you feel mentally fatigued? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all fatigued	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely fatigued

16. Do you feel sleepy or drowsy? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all sleepy or drowsy	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely sleepy or drowsy

17. Do you feel active and energetic? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all active	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely active

18. How difficult was the task? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Very Easy	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Very difficult

Post Task 2 (2-Back)

DIRECTIONS: You are asked to choose a number on each of the following questions to indicate how you are feeling, RIGHT NOW.
For example, if you have not eaten since yesterday, in response to the question, how hungry are you, you might want respond extremely hungry. You might want to respond by choosing a number close to 10, as shown below:

19. How tired do you feel overall? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all tired	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely tired

20. How physically fatigued do you feel? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all fatigued	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely fatigued

21. Do you feel mentally fatigued? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all fatigued	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely fatigued

22. Do you feel sleepy or drowsy? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all sleepy or drowsy	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely sleepy or drowsy

23. Do you feel active and energetic? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all active											Extremely active

24. How difficult was the task? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Very Easy											Very difficult

Post Task 3 (Physical)

DIRECTIONS: You are asked to choose a number on each of the following questions to indicate how you are feeling, RIGHT NOW.
For example, if you have not eaten since yesterday, in response to the question, how hungry are you, you might want respond extremely hungry. You might want to respond by choosing a number close to 10, as shown below:

25. How tired do you feel overall? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all tired											Extremely tired

26. How physically fatigued do you feel? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all fatigued											Extremely fatigued

27. Do you feel mentally fatigued? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all fatigued											Extremely fatigued

28. Do you feel sleepy or drowsy? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all sleepy or drowsy											Extremely sleepy or drowsy

29. Do you feel active and energetic? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all active											Extremely active

30. Do you have difficulty breathing right now? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all											A lot

31. How difficult was the task? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Very Easy											Very difficult

Post Task 4 (0-Back)

DIRECTIONS: You are asked to choose a number on each of the following questions to indicate how you are feeling, RIGHT NOW.
For example, if you have not eaten since yesterday, in response to the question, how hungry are you, you might want respond extremely hungry. You might want to respond by choosing a number close to 10, as shown below:

32. How tired do you feel overall? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all tired											Extremely tired

33. How physically fatigued do you feel? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all fatigued	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely fatigued

34. Do you feel mentally fatigued? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all fatigued	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely fatigued

35. Do you feel sleepy or drowsy? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all sleepy or drowsy	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely sleepy or drowsy

36. Do you feel active and energetic? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Not at all active	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Extremely active

37. How difficult was the task? *

Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Very Easy	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	Very difficult

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BIOGRAPHICAL STATEMENT

Varun Ajay Kanal was born on the 6th of August 1991 in erstwhile Bombay, India. After completing his initial education, in 2009, he embarked on his journey to attain a Bachelor's degree in Instrumentation Engineering from the University of Mumbai. He graduated in 2013. Following his passion and interest in engineering and biology, he joined the University of Texas at Arlington to pursue a Master's degree in Biomedical Engineering soon after. He graduated in 2015.

During his time as a Master's degree candidate, he began his journey into the field of research by writing his thesis on sleep apnea, titled 'An Investigation Of The Covariations Between Variations In Exhaled Carbon Dioxide And Cerebral Blood Flow Levels During Apnea'. In 2016, he enrolled in a Ph.D. program in Computer Science at the University of Texas at Arlington.

He joined the HERACLEIA - Human-Centered Computing Lab in the Computer Science and Engineering Department under the supervision of Dr. Fillia Makedon. Here, he worked on multiple NSF-funded projects as a Graduate Research Assistant. As a Teaching Assistant, he assisted in multiple project-related labs and classes, also guiding students in their projects. Varun was also invited to present lectures in the 'Advanced Topics in Human-Computer Interaction' class. During his time as a Ph.D. candidate, Varun mentored multiple undergraduate REU students, thoroughly enjoying his stint in academics. In 2021, he successfully presented his Ph.D. thesis.

Varun's research revolves around creating medical systems and devices using physiological sensors. He also continues to work in the area of signal processing, machine learning, sensors, robotics, and statistics, among others. Varun has been accepted into a Post-Doctoral Research Fellowship at the Food and Drug Administration under the supervision of Dr. Ramin Bighamian, and will be involved in building mathematical models of physiological systems.