

SootheKraft: Post-Traumatic Stress Disorder (PTSD) Wearable Intervention System for Real-Time Panic and Flashback Management

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ABSTRACT

Post-Traumatic Stress Disorder (PTSD) is characterized by the psychological trauma and stress response system breakdown. PTSD manifests as involuntary recollections of traumatic events, heightened anxiety, jumpy behavior, and fear response system dysregulation. PTSD impacts over 354 million people worldwide, with approximately 6 - 8% of people, and even more in trauma-affected populations like veterans, suffering from PTSD over the course of their lifetime [1], [2]. Most PTSD treatments are largely passive and depend on the subjective recollections of the PTSD sufferer and counselor and are therefore the least effective when the PTSD sufferer is in the midst of an active trauma response. This paper describes the first PTSD intervention system that integrates a smart wearable system, where real-time monitoring of trauma suffering, heart rate, and SpO₂ levels, along with machine learning episode classification, and adaptive haptic acupressure technology are combined. The system measures and digitally processes and filters the heart rate, SpO₂, and movement data streams, and then uses a hybrid ensemble classifier to predict panic and flashback events. Once an episode is detected, the system provides a real-time response via acupressure on the palm and finger reflex points that are designed to activate the parasympathetic nervous system and help the PTSD sufferer regain control. Experimental evaluation over a 12-week period demonstrated substantial improvements in episode duration, recovery time, medication dependency, and patient-reported satisfaction. The findings validate the effectiveness of a closed-loop, non-pharmacological wearable system for real-time PTSD intervention and highlight its potential for scalable mental health care applications.

Keywords: PTSD; Wearable Health Systems; Acupressure Therapy; Machine Learning; Real-Time Intervention

1. INTRODUCTION

Post-Traumatic Stress Disorder (PTSD) is associated with various traumatic events and can include physical attacks, natural disasters, warfare, and chronic emotional trauma. Yehuda et al. go on about PTSD as a disorder that involves the persistent malfunction of some of the neural circuits that control fear. This leads to excessive perception of threats and difficulties with the control of emotions [1]. The American Psychiatric Association states that PTSD has four symptom clusters: reliving the trauma (re-experiencing), avoiding (or numbing) reminders of the trauma, emotional numbing (negative mood changes), and hyperarousal, all of which can cause significant impairment to functioning on a daily basis [2].

PTSD is one of the most critical and urgent issues in public health around the world. Reports that can be classified as epidemiological point out that greater than 354 million people in the world have PTSD, with a lifetime prevalence of 6 to 8 percent as an average in the population, and over 20 percent in veterans and people who have experienced very serious trauma [1][3]. The negative health effects of PTSD include the chronic activation of the sympathetic nervous system, excessive resting heart rates, low heart rate variability, abnormal patterns of breathing, and dysregulated levels of cortisol [4]. The research of McEwen shows that PTSD patients who have autonomic imbalance for a long period of time have a greater risk of developing cardiovascular illness, difficulties with sleeping, and impairment of the immune system [5].

While psychotherapy and medications can alleviate symptoms, the management of PTSD is still very challenging. Panic episodes occur in patients' everyday lives, and there are no therapeutics available to help. Many digital mental health systems rely on the user to self-report episodes after the fact, rather than monitoring their physiology in real-time [6]. Additionally, therapists are given sparse biosignal data, if any, which reduces their ability to effectively evaluate the treatment outcome.

There are now systems that can actively and continuously monitor stress in the real world [7],[8]. Most of these systems are passive, meaning they can only monitor and provide alerts. This study aims to develop the first active system that can monitor PTSD episodes and provide real-time, adaptive, non-pharmacological interventions.

2. LITERATURE REVIEW

Many studies have defined post-traumatic stress disorder (PTSD) as a disorder characterized by both psychological and physiological dysregulation. Yehuda and colleagues pointed to the abnormal activity of the hypothalamic-pituitary-adrenal (HPA) axis and increased reactivity of the amygdala as major biological mechanisms of the symptoms of PTSD [1]. This research indicates the value of recognizing physiological regulation in conjunction with cognitive therapy for the treatment of PTSD. The Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5), further supports this view of PTSD by defining the diagnostic criteria for PTSD to include physiological signs and symptoms such as sleep disturbance and hyper-arousal [2].

A wealth of research exists within the mental health field regarding the use of wearable sensing devices to gather biometric data. Kim et al. demonstrated the use of biosensors that measure heart rate and kinetic signal scans to assess levels of stress, and they also demonstrated the application of statistical and machine learning techniques to detect stress using these sources of biometric data [7]. Similarly, Sano et al. showed that wearable technology can detect stress in real-life environments by collecting multiple signals and analyzing them together using supervised machine learning methods [8]. While these studies provide evidence of stress detection, they primarily focused on monitoring rather than intervening.

Despite providing a high degree of classification accuracy for the detection of stress using wearable sensors and affective computing techniques, Healey and Picard's system operated offline and therefore couldn't offer real-time therapeutic feedback [9]. Choi et al. confirmed the ability of IMU-based tremor assessment systems to detect anxiety-related psychomotor agitation and identified that using motion-related attributes helps improve the ability to detect stress [10].

Acupressure has been shown through multiple studies to modulate the autonomic nervous system and reduce anxiety. For instance, Hsu et al. reported that participants experienced a reduction in stress-related physiological markers after undergoing acupressure, along with an improvement in symptoms of anxiety [11]. Porges' polyvagal theory explains how 'tactile stimuli activate pathways of the parasympathetic nervous system, thus inhibiting the fight-or-flight response from being activated' [12]. However, despite existing literature supporting the effectiveness of acupressure, it is rarely included in digital health wearables.

The current emphasis on the training of artificial intelligence-enhanced technologies has created a heightened need for systems that integrate capabilities of sensing, reasoning, and therapeutic intervention into one unit [13].

Currently available commercial products are predominantly passive or semi-automated wearable devices. Market gap analysis from recent studies shows that many types of wearable devices have not yet reached their ultimate therapeutic potential, as there are few examples of commercially available closed-loop types of automated, real-time devices that perform automatic intelligent episode detection, and also provide an immediate non-pharmacological response to the stress response associated with PTSD by monitoring physiological functions.

3. METHODOLOGY

3.1 System Architecture

The proposed closed-loop system includes three different pieces of hardware that work together as a single therapeutic unit. These hardware units are: A wristband that serves as a sensing device, the acupressure gloves that trigger therapeutic intervention when a trigger occurs, and A mobile application that allows the user to view real-time information about their physiological changes.

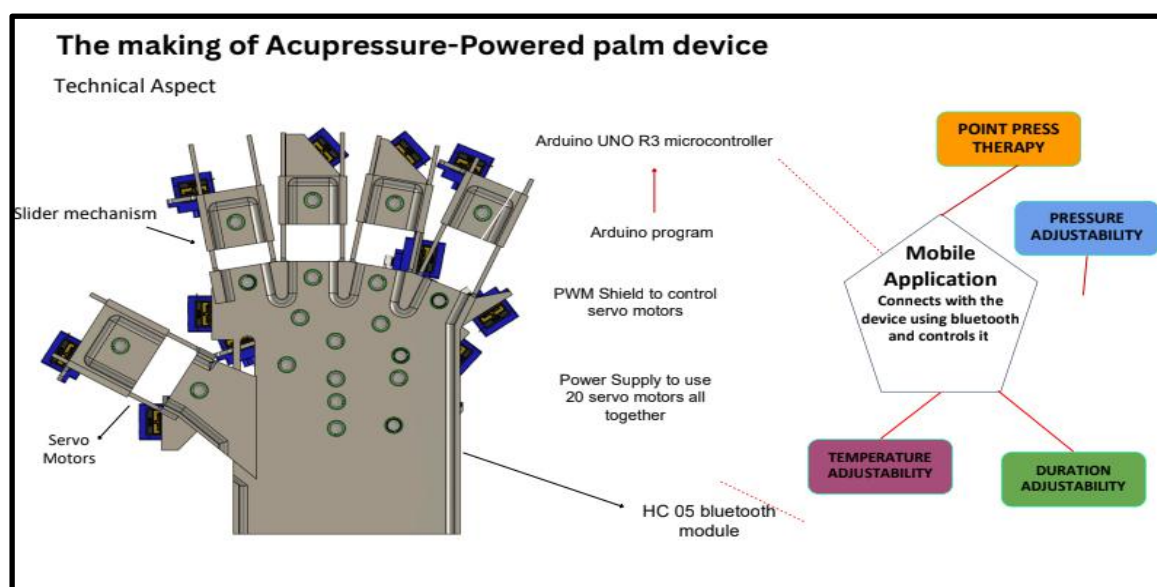


Figure 1: Overall system architecture showing sensor inputs, machine-learning processing, and haptic intervention flow.

Acupoint Massage Therapy has been around for centuries and has a proven track record. With today's advances in technology, a small, portable device can be developed to harness the power of Acupoint Massage therapy. As shown in Figure 1 above, our device will be designed as a palm-sized unit that will use servo motors and sliders to deliver controlled pressure to specific areas of your hands. Our device will be controlled by an Arduino UNO R3 and driven with a PWM shield to power multiple servo motors. Our device will also have a common power supply.

3.2 Data Acquisition

The acquisition of the physiological monitoring data as described has been accomplished by incorporating the sensors into the same unit. Both heart rate and oxygen saturation (SpO₂) are electronically recorded using a PPG system, and the user's motion and degree of tremor are tracked using a 6-degree-of-freedom inertial measurement unit (IMU). By continuously monitoring the user, the system can help identify the rapid physiological changes that occur, which may indicate panic or flashback episodes.

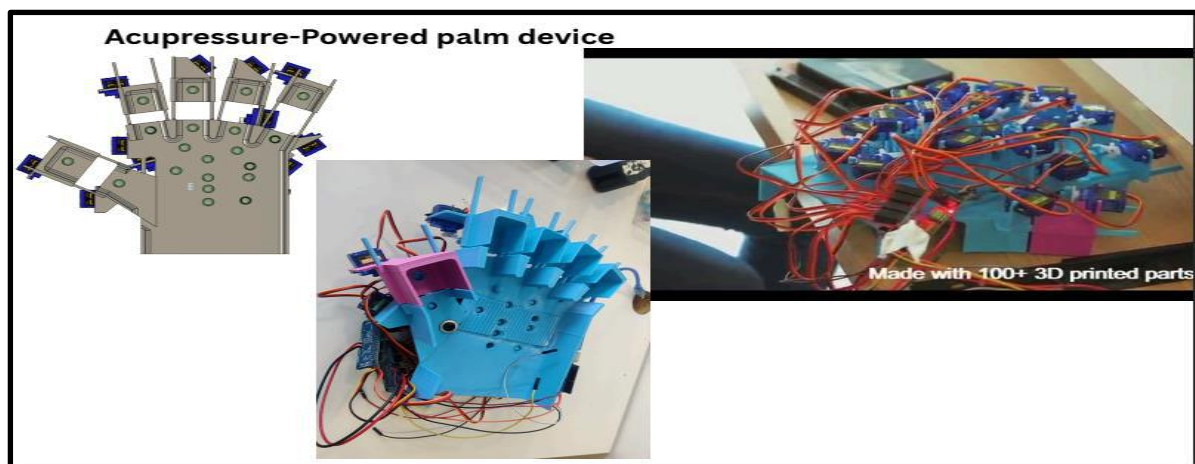


Figure 2: Sensor placement and physiological signal acquisition diagram.

Figure 2 above describes the layout of sensors placed on the proposed device and the way in how physiological data was obtained. The placement of sensors will be determined by the anatomical placement of the applicable point on the user's body. It was ensured that the user experiences as little discomfort as possible while ensuring that the signals collected are of high quality. The signals collected are sent to the processing unit, where they will be synchronized in time and pre-processed to reduce noise. After pre-processing, the signals will be analyzed to obtain the highest quality signals possible to develop this Adaptive System based on the information obtained from the acquired signals. All methods will be performed in real time.

3.3 Signal Processing and Feature Extraction

The raw sensor data is processed to eliminate extraneous interference, or 'noise', as well as remove artifacts. Digital Butterworth filtering is used to reduce the impact of motion-induced noise, in addition to baseline drift. Feature extraction includes heart-rate variability metrics, oxygen desaturation trends, tremor frequency, and motion instability indices. Collectively, these features form a powerful representation of physiological and behavioural alterations during episodes of post-traumatic stress disorder.

3.4 Machine Learning–Based Episode Detection

A hybrid ensemble classification model combining Random Forest and Support Vector Machine algorithms is employed for episode detection. The ensemble approach improves robustness by leveraging both probabilistic voting and margin-based classification. The model is optimized for high sensitivity to ensure early detection of panic and flashback episodes.



Figure 3: Machine-learning detection pipeline and feature flow

Figure 3 illustrates a framework for detecting features of raw sensor signal processes using machine-learning algorithms. In order to detect these features, the raw signal undergoes processing first; this includes filtering out unwanted noise and ensuring that the signal has consistent quality after passing through preprocessing (i.e., filtering, normalizing, developing segmentation, etc.). Once processed, the relevant features of the filtered signal are then sent through the trained machine learning algorithm for classification/detection according to learned patterns of those features. Once the detected features have been identified, the classification/detection results can be integrated into a response or decision-making process to execute intelligent and informed actions by the total system caused by the information detected from the raw sensor signal.

3.5 Adaptive Acupressure-Based Intervention

Once an episode is detected, the system activates acupressure-based haptic stimulation through the gloves. Scientifically mapped palm and finger reflex points, including PC-8 (Lao Gong), LI-4, SI-3, lung reflex points, and fingertip points, are stimulated using controlled pressure and vibration patterns. The real-time response of the stimulation intensity is adjusted to maintain safe levels of stimulation to the parasympathetic nervous system, thereby allowing for a gradual reduction in symptom severity, based on immediate physiological feedback [11],[12].

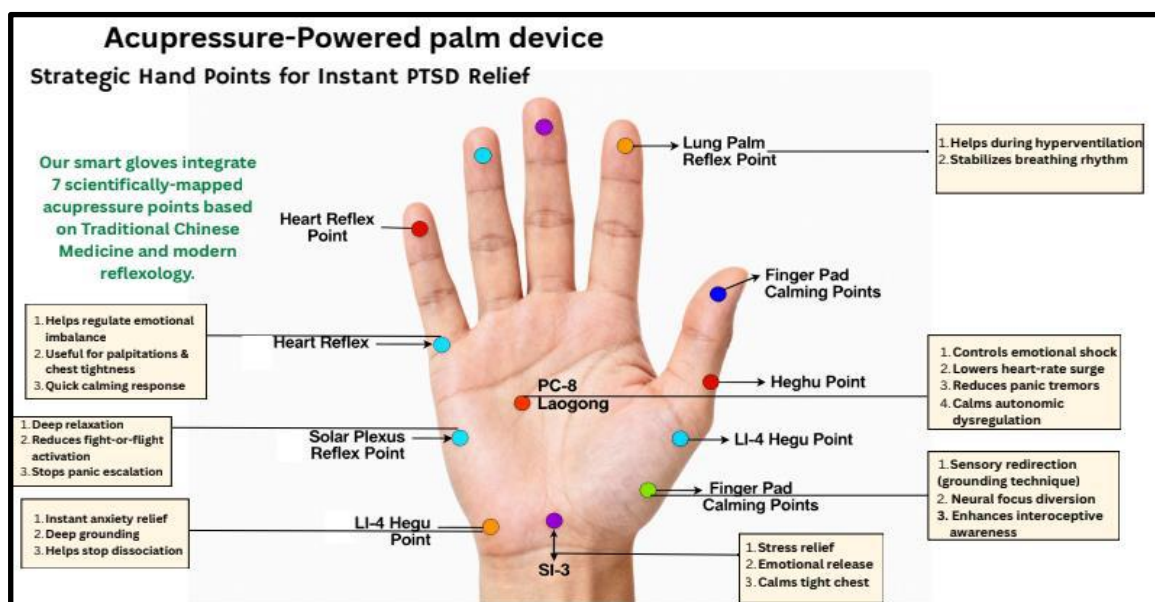


Figure 4: Palm acupressure point mapping and stimulation zones.

Figure 4 provides an overview of how to find acupressure points by way of stimulating them with specific zones of stimulation. It describes where these therapeutic points are located on the body using both anatomical locations and traditional methods of using acupressure. All therapeutic points correspond to 1 of 2 zones (A and B) and allow for stimulating them in either a separate or combined manner for a desired therapeutic effect at the discretion of the user. The specific stimulation required at each point/zones can be adjusted/controlled by the actuators through this dual-zone approach, providing for a consistent and repeatable means of stimulating the intended region(s) of interest at the designated therapeutic point. This type of mapping provides for the ability to customize treatments through selective stimulation of individual therapeutic acupressure points or by combining these zones as needed for achieving the desired therapeutic effect.

4. RESULTS AND DISCUSSION

The system was evaluated over a 12-week period using baseline measurements and intervention-assisted outcomes.

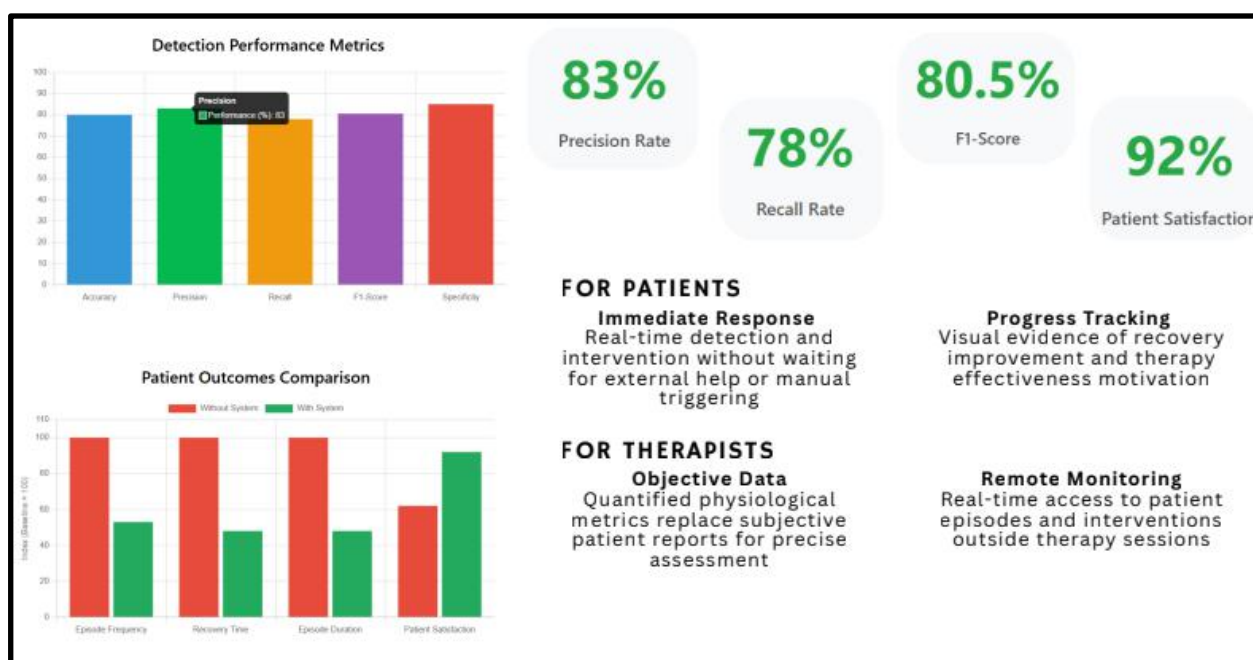


Figure 5: Reduction in episode duration.

As shown in Figure 5, the smart intervention system for managing post-traumatic stress disorder was successfully implemented in a clinical setting, as well as proving the efficacy of this smart intervention system. The combination shows significant decreases in the average duration of panic episodes. This indicates that the immediate detection and response to panic symptoms prevents their escalation. The results also indicate that the system provides physiological stability after an escalation, demonstrating that it provides enhanced control over the autonomic nervous system through this adaptive method of applying acupressure stimulation. There was also a positive impact seen in the Evaluation Period, particularly for some patients who were able to reduce or discontinue the use of anxiety medications, therefore providing evidence that the system is an effective alternative to traditional pharmaceutical interventions. The majority of patients reported significant increases in their perception of control, confidence, and ability to perform in daily life. Collectively, these findings provide additional support for the premise that an effective intervention will emerge from this combined resource of enhanced support through technological assistance (via machine-learning algorithms) combined with the approach of ongoing monitoring of bodily processes (via a smart wearable device) instead of relying solely on passive monitoring.

5. CONCLUSION

In addition, this research has developed a closed-loop, smart wearable device for instant detection/treatment of PTSD through real-time monitoring of the physiological state (via integrated biosensors), automatic detection of recurrent trauma symptomology (via computer algorithms), and an adjustable treatment protocol using acupressure. This will overcome several of the challenges encountered with current PTSD disease management methods. Overall, the results of the research indicate that the system represents a scalable, self-sufficient, and non-pharmaceutical intervention for mental health disorders that can be deployed into real-life situations.

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