State-Space Modeling and Fuzzy Feedback Control of Cognitive Stress

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***Abstract*— "Distress" or a substantial amount of stress may decrease brain functionality and cause neurological disorders. On the other hand, very low cognitive arousal may affect one's concentration and awareness. Data collected using wrist-worn wearable devices, in particular, skin conductance data, could be used to look into one's cognitive-stress-related arousal. Our goal here is to present excitatory and inhibitory wearable machine-interface (WMI) architectures to control one's cognitive-stress-related arousal state. We first present a model for skin conductance response events as a function of environmental stimuli associated with cognitive stress and relaxation. Then, we perform Bayesian filtering to estimate the hidden cognitive-stress-related arousal state. We finally close the loop using fuzzy control. In particular, we design two classes of controllers for our WMI architectures: (1) an inhibitory controller for reducing arousal and (2) an excitatory controller for increasing arousal. Our results illustrate that our simulated skin conductance responses are in agreement with experimental data. Moreover, we illustrate that our fuzzy control can successfully have both inhibitory and excitatory effects and regulate one's cognitive stress. In conclusion, in a simulation study based on experimental data, we have illustrated the feasibility of designing both excitatory and inhibitory WMI architectures. Since wearable devices can be used conveniently in one's daily life, the WMI architectures have a great potential to regulate one's cognitive stress seamlessly.**

I. INTRODUCTION

Stress is an undeniable part of life. Long term exposure to high amounts of stress-related arousal could lead to major health problems; on the other hand, low arousal could result in lethargy and boredom[1], [2]. Over 60% of Americans feel that stress affects their work performance negatively [3]. Considering the fluctuations in one's cognitive-stress-related arousal state, and that brain performs better when one's cognitive state is in a moderate range (neither too high nor too low) [1], stress regulation has received a lot of attention.

Recently, there have been various studies that have used different physiological data to manage stress [4], [5], [6], [7]. Recent advances in wrist-worn wearable device technologies have provided the opportunity to monitor one's physiological signals. These wrist-worn wearable devices can conveniently provide continuous physiological data monitoring capabilities [8], [9], [10]. Among the data that can be collected via such wearable devices, skin conductance data includes information about one's cognitive-stress-related arousal [11], [12], [13], [14], [15], [16]. In the presence of external environmental stimuli or internal mental stimuli, there are small variations in the activity of the sweat glands [15]. As a result, skin electrical characteristics will change. Such fluctuations are indicated in the skin conductance response (SCR), which can be measured using wearable devices. It has been validated in experimental studies that SCR carries information about one's cognitive-stress-related arousal [17], [9].

In this research, we aim to use wearable machine interface (WMI) architectures to control cognitive-stress-related arousal. Figure 1 illustrates an example of such closed-loop system. Here, we focus on skin conductance data which can be collected using wrist-worn wearable devices [14], [18]. We first present a model to simulate SCR events both in cognitive stress and relaxation tasks. Next, we estimate the hidden cognitive-stress-related arousal state using Bayesian filtering. Finally, we implement fuzzy control structure [19], [20], and present our closed-loop results. In particular, we consider one open-loop, one inhibitory closed-loop, and one excitatory closed-loop example to show the performance of our WMI architecture.

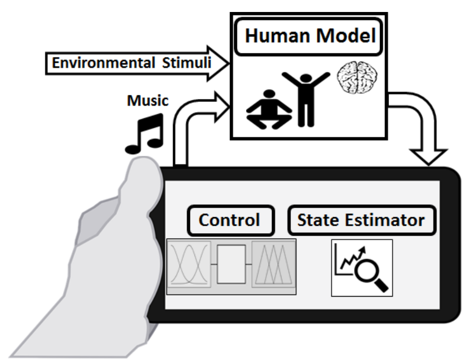

Fig. 1. **Wearable Machine Interface Architecture.** A wrist-worn wearable device measures skin conductance data from the human in the loop as a function of the environmental stimuli. Then, a decoder estimates the cognitive-stress-related arousal based on the measured SCR events. Finally, the controller excites or inhibits cognitive-stress-related arousal by playing music to close the loop and regulate the cognitive stress level.

II. METHODS

A. Experiment

In this research, we develop our human model based on the skin conductance data from the Non-EEG Dataset for Assessment of Neurological Status [18], [14], [21]. In this experiment, subjects performed physical, cognitive, emotional stress, and relaxation tasks. Here, we focus on two

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tasks: cognitive stress and relaxation. The cognitive stress task included instructions, an arithmetic task, and a stroop test. In particular, we investigate the arithmetic cognitive stress task. Arithmetic task includes counting backward by 7 seconds starting from 2485. This task lasts for 5 minutes followed by 3 minutes of relaxation. In this study, we are using the data associated with subject number 8 [18].

B. Human Model

We present a state-space representation for the cognitive-stress-related arousal [14]:

$$x_{k+1} = x_k + u_k + \eta_k \tag{1}$$

where x_k is the hidden cognitive-stress-related arousal state, u_k is the control signal and $\eta_k = s_k + \nu_k$ is the environmental input at k^{th} time step; s_k is the environmental stimuli, and ν_k is the process noise $\left(\nu_k \sim \mathcal{N}(0, \sigma_\epsilon^2)\right)$ [14]. Here we set $\sigma_\epsilon = 0.00034$. Similar to [14], we model the SCR events using the Bernoulli distribution:

$$P(n_k|q_k) = q_k^{n_k}(1-q_k)^{1-n_k} \tag{2}$$

where q_k is computed by the following logistic relationship:

$$q_k = \frac{1}{1+e^{-(\beta+x_k)}} \tag{3}$$

This model relates the probability q_k of observing a SCR event n_k to the cognitive-stress-related arousal state x_k as well as a person-specific baseline parameter β. In this study, we follow [14] and set $x_0 = 0$ and $q_0 = 0.11$ for subject number 8 [18] (i.e. $\beta = -2.19$).

C. Cognitive State Estimation

Given the observed SCR events n_k, we would like to estimate x_k and the corresponding variance term σ_k [14]. Using a Bayesian filter [22], [23], we estimate the hidden cognitive state:

$$\hat{x}_k = \hat{x}_{k-1} + (\hat{\sigma}_{k-1}^2 + \sigma_\epsilon^2)\Big(n_k - \frac{1}{1+e^{-(\beta+\hat{x}_k)}}\Big) \tag{4}$$

$$\hat{\sigma}_k^2 = \Big(\frac{1}{\hat{\sigma}_{k-1}^2 + \sigma_\epsilon^2} + \frac{e^{(\beta+\hat{x}_k)}}{(1+e^{(\beta+\hat{x}_k)})^2}\Big)^{-1} \tag{5}$$

where $\hat{x}_k$ is the estimated hidden cognitive state and $\hat{\sigma}_k$ is the corresponding variance. We initialize $\hat{x}_0$ and $\hat{\sigma}_0$ using the Expectation Maximization algorithm presented in [14].

D. Environmental Stimuli Model

To model the environmental stimuli, we consider two environmental stimuli models, one for the cognitive stress task and one for the relaxation task. In particular to find the environmental stimuli model, we use the experimental skin conductance data in [18], the state estimates in [14], and $\eta_k = s_k + \nu_k$. Then, we obtain a sinusoidal harmonic model for the cognitive stress arithmetic task (i.e., high arousal stimuli), and an exponential model for the relaxation task (i.e., low arousal stimuli). The environmental stimuli model s_k for cognitive stress is noted by s_k^c and is given as:

$$s_k^c = \sum_{n=1}^{N} \alpha_n cos(\omega_n k + \gamma_n) \tag{6}$$

where N is the number of the harmonics, and α_n, ω_n, and γ_n for $n = 1, .., N$ are the amplitude, frequency, and phase shift of each of the harmonics, respectively. Here, we use 50 harmonics to model the stress stimuli ($N = 50$). The environmental stimuli model s_k for relaxation is noted by s_k^r and is given as:

$$s_k^r = ae^{bk} \tag{7}$$

We assume at the transition times between cognitive stress and relaxation tasks, the sinusoidal harmonic model equals the exponential model.

E. Control Design

To control the estimated cognitive state, we design a fuzzy controller. Fuzzy logic provides a great connection between linguistic concepts and the real world [19], [20], [24], [25]. In this study, the estimated cognitive state is the input to the fuzzy controller and the control signal u_k in Equation (1) is the the output of the fuzzy controller. Rule-base structure of the fuzzy controller is derived from our knowledge of the system [25]. We define the rules as:

- If the estimated cognitive state is *high arousal*, then control is *inhibitory*.
- If the estimated cognitive state is *low arousal*, then control is *excitatory*.
- If the estimated cognitive state is *neutral*, then control is *neutral*.

As it is observed in these rules, there are linguistic variable that should be converted to the crisp values. We then define our corresponding membership functions to design the fuzzy control. Figure 2 depicts the membership functions corresponding to the input and the output of our fuzzy controller. In our fuzzy controller, for fuzzy inference, we use *Mamdani inference engine* [26], and for defuzzification, we use the *centroid* method [20].

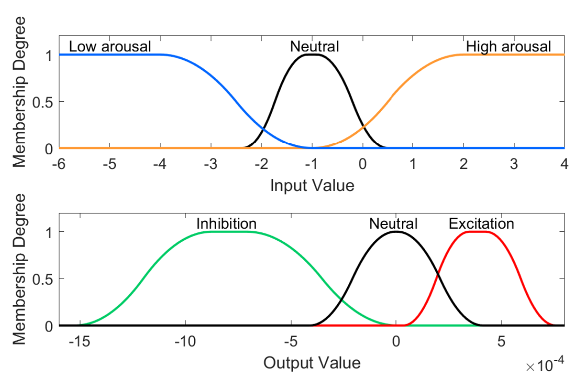

Fig. 2. **Input and Output Membership Functions.** The top-panel shows the membership functions for the input (i.e. estimated cognitive-stress-related arousal state). The bottom-panel shows the membership functions for the output (i.e. control signal u_k).

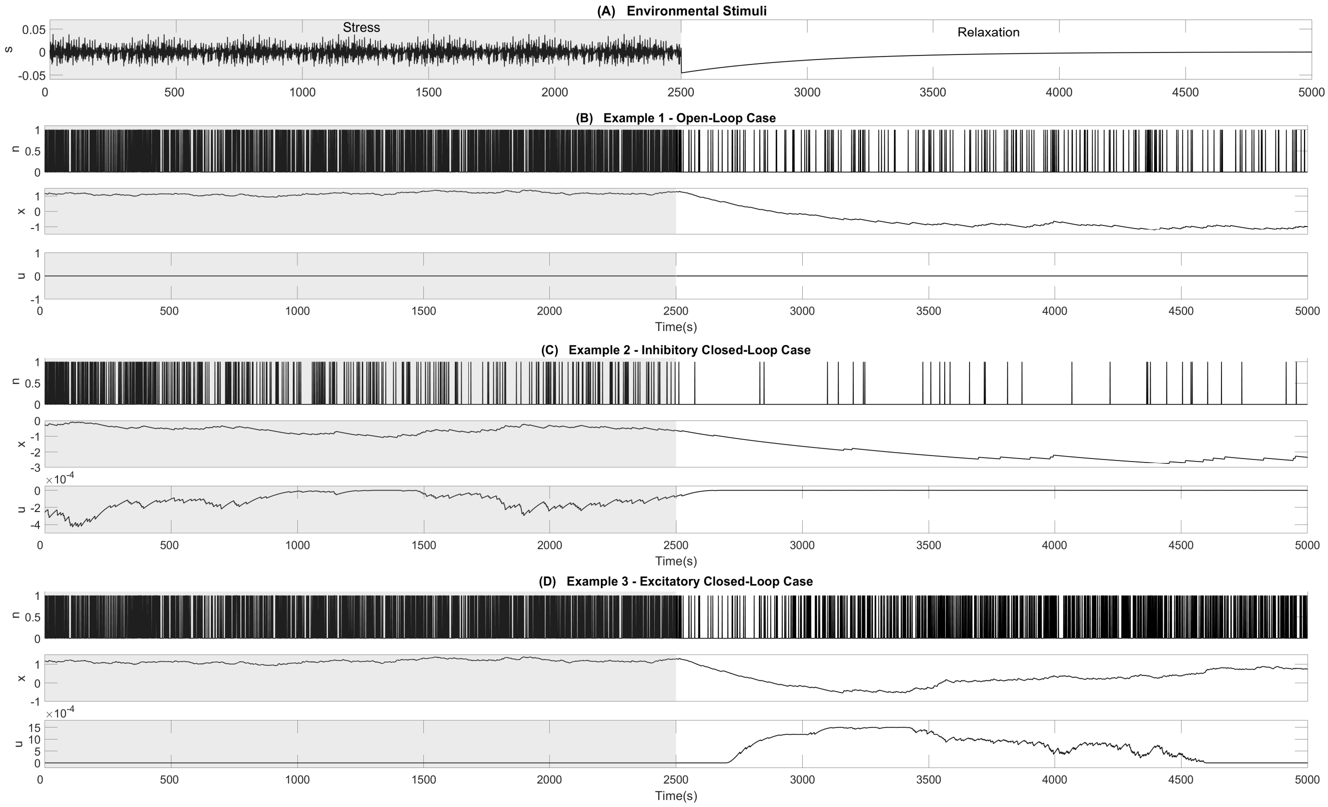

Fig. 3. **WMI Architecture Results.** Panel A displays the simulated environmental stimuli. Panel B shows open-loop cognitive state tracking. Panels C and D show inhibitory and excitatory closed-loop control and cognitive state tracking, respectively. In panels B, C, and D: the top sub-panel shows the SCR events from the human model, the middle sub-panel displays the estimated cognitive state, and the bottom sub-panel depicts the control signal. The grey background belongs to the high arousal environmental stimuli (i.e. the cognitive stress task) and the white background implies the low arousal environmental stimuli (i.e. the relaxation task).

III. Results

In this section, we present our results for three different cases: open-loop, inhibitory closed-loop, and excitatory closed-loop. For each case we consider two environmental stimuli models: (1) cognitive stress, and (2) relaxation (please see panel A of Figure 3).

A. Example 1 - Open-loop Case

We aim to track one's cognitive-stress-related state when no control input is applied ($u_k = 0$). In panel B of Figure 3, it is observed that the estimated cognitive state declines during the relaxation period. Moreover, the number of SCR events significantly decrease during relaxation compared to the stress task.

B. Example 2 - Inhibitory Closed-Loop Case

By designing the inhibitory closed-loop architecture, our system detects high arousal (i.e cognitive stress) and the control signal decreases the stress level. As observed in panel C of Figure 3, during the cognitive stress environmental stimuli (first half of the simulation study), the control is leading to fewer SCR events and lower estimated cognitive-stress-related arousal compared to the open-loop case (first half of panel B of Figure 3). Since this closed-loop controller is inhibitory and the second half of the simulation study is associated with low arousal, the control goes to zero during the relaxation period ($u_k = 0$).

C. Example 3 - Excitatory Closed-Loop Case

By designing the excitatory closed-loop architecture, our system detects low arousal and the control signal increases the arousal. As observed in panel D of Figure 3, during the low arousal environmental stimuli (second half of the simulation study), the control is leading to more SCR events and higher estimated cognitive-stress-related arousal compared to the open-loop case (second half of panel B of Figure 3). Since this closed-loop controller is excitatory and the first half of the simulation study is associated with high arousal, the control is zero during the cognitive stress period ($u_k = 0$).

IV. Discussion and Conclusions

With the goal of cognitive stress modelling and control using WMI architectures, we first simulate SCR events using a state-space model, and then use a fuzzy logic approach to control cognitive stress. We illustrate that we can achieve both inhibitory and excitatory control. Our simulated results indicate that our proposed method has great potential to be implemented in wrist-worn wearable devices to be used in daily life. One potential application is automated relaxation when an individual is experiencing high levels of stress. Another potential application is automated arousal when an individual is depressed.

In this study, we provided a model for the environmental stimuli during cognitive stress and relaxation. We presented a human model and used a Bayesian filter to estimate the cognitive state. Finally, we designed a fuzzy controller that can successfully achieve inhibitory and excitatory closed-loop control. For example, environmental conditions such as work pressure could result in cognitive stress and negatively affect the individual's productivity. In this case, the proposed inhibitory WMI architecture could be used to inhibit the undesired cognitive stress that leads to loss of productivity. Another example is the case that an individual is not cognitively engaged and focused. In this case, the proposed excitatory WMI architecture could be used to result in cognitive arousal and help the individual become more engaged with their environment. The proposed fuzzy control approach is flexible in different environmental conditions and also has a simple structure. In such WMI architectures, a wearable device collects related physiological data, a decoder estimates the cognitive stress and a controller brings the cognitive stress to the desired range by playing music for actuation and closing the loop.

Future directions of this research include modeling environmental stimuli for different emotional, physical, and cognitive stress tasks based on various subjects to create a more comprehensive human model as a function of environmental conditions.

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