2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

A State-space Investigation of Impact of Music on Cognitive Performance during a Working Memory Experiment

Md. Rafiul Amin, *Student Member, IEEE*, Maryam Tahir, and Rose T. Faghih*, *Member, IEEE*

Abstract— **Stress has effects on productivity and performance. Poor stress management may lead to reduced productivity and performance. Non-invasive actuators such as music have the potential to effectively regulate stress. In this study, using a state-space approach, we obtain a performance state to investigate the performance during a working memory task while playing two different types of music in the background. In our experiments, participants performed a working memory task while listening to calming and vexing music of their choice. We utilize the binary correct/incorrect response and the continuous reaction time of the response from the participants to quantify the performance. The state-space quantification reveals that vexing music has a statistically significant positive impact on the obtained performance state. This indicates the feasibility of designing non-invasive closed-loop systems to regulate stress for maximizing performance and productivity.**

I. INTRODUCTION

Stress is a part of daily life in workplaces and schools, and it can impact work performance and productivity. Over 60% of Americans report that stress hurts their work performance [1]. Arousal plays a key role in work performance and stress. Low arousal can lead to boredom and laziness, which leads to poor performance. On the other hand, high arousal can lead to anxiety and stress and lead to poor performance. There is a need for optimizing arousal to obtain the best possible performance. External non-invasive stimuli such as music are non-invasive solutions that can improve productivity and work performance as it impacts the mood, arousal, mental workload, and working memory capacity of an individual.

Background music can impact performance by directly influencing the mood or arousal of an individual. Arousal is defined by physical activation and mood refers to emotions. There can be an increase or decrease in arousal caused by the tempo of the music [2]. Little arousal can lead to less attention in the learning process, while too much can lead to anxiety and feeling distracted. There needs to be an optimal level of arousal for learning to occur. Background music can also influence mood. A positive mood can improve learning while a negative mood can hinder learning [2].

Working memory (WM) describes a system that can preserve sensory information for processing and integration and allows for cognitive understanding [3]. WM is critical to our everyday life and cognitive functions, such as problem-solving, decision making, learning, executive function, and behavior. Mental workload refers to the exertion of the cognitive system. Tasks that pose a higher cognitive demand call for a higher mental workload, and states of increased mental workload occur with an increased level of difficulty of the working memory task [3]. Listening to music can impact working memory and performance in the task.

According to Lehmann et al. [2], tasks that pose a lower burden on working memory, such as recall, are not influenced by background music; however, tasks that pose a higher burden on working memory, such as comprehension, are influenced by background music. Participants reached higher levels of learning when there was no background music present. Since music is processed first, there is not enough working memory capacity left to work on a cognitively demanding task, such as comprehension [2].

The type of music can have a direct impact on working memory and task performance. A study done on the impact of music on the performance of n-back task—a type of WM task—revealed that rock music can have a negative impact on the performance of the n-back task while no music or listening to country or jazz music can lead to the participant performing well on the n-back task [4]. Another study also demonstrated that rock music delayed the participants response to the task in comparison with noise, silence, country or jazz music [5]. The study also uncovered that background noise increased the participants error rate in comparison with the other conditions. Rock music and traffic noise were found to have a negative impact on men's cognitive task performance [5]. These studies explore how the presence or absence of music and the type of music impact the learning or working memory capacity of an individual, however, limited research has been done on the impact of music on working memory during n-back tasks. Only a few studies investigated the impact of listening to different types of music (calming vs. vexing) on learning and working memory.

Our study aims to explore how vexing and calming music can impact working memory through the use of n-back tasks. We follow a state-space approach to obtain a hidden performance state based on the observations similar to [6]–[14]. We utilize binary and continuous measurements to quantify the working memory task performance. Binary measurements are the sequence of correct and incorrect responses given by the participant, and continuous measurements are the time

This work was supported in part by by the U.S. National Science Foundation under Grants 1942585 – CAREER: MINDWATCH: Multimodal Intelligent Noninvasive brain state Decoder for Wearable AdapTive Closed-loop arcHitectures, 1755780 – CRII: CPS: Wearable-Machine Interface Architectures, and 1757949 – REU Site: Neurotechnologies to Help the Body Move, Heal, and Feel Again.

M. R. Amin, M. Tahir and R. T. Faghih are with the University of Houston, Houston, TX, USA (correspondence e-mail: rtfaghih@uh.edu). Rose T. Faghih served as the senior author.

it takes for the participant to give a response (i.e., reaction time or response time). Few studies investigate the impact of music on working memory and learning through a combined analysis of continuous and binary data. In this study, we propose a state-space model to represent a hidden continuous performance state and its dynamics similar to the approach used in quantifying a learning state [15]. Next, we leverage an expectation-maximization (EM) framework composed of a fixed-interval smoother (FIS) and a maximization step to estimate the performance states and the corresponding parameters to quantify the states. Finally, we perform statistical analysis on different performance matrices to identify how music influences performance during different n-back tasks.

II. METHODS

A. Experiment

In this research, the impact of calming and vexing music on working memory is studied through the use of n-back tasks. This study involved six participants (four females and two males) between the ages of 22-25; two sessions with similar tasks occurred. This study was conducted at the University of Houston, Houston, Texas, USA, and approved by the Institutional Review Board. The experiment is designed with two sessions, one with calming music and another with vexing music. Both music tracks were selected by the participants. In each session, participants performed n-back task [16], [17]. A single trial of an n-back task consists of sequences of letters. For each stimulus during n-back task, the participants have to answer whether the present stimulus matches the stimulus presented n stimulus back [16], [17]. Participants press the target button if the current stimulus matches the n^{th} previous stimulus and the non-target button otherwise. Each session consisted of 8 trial blocks of 1-back tasks and 8 trial blocks of 3-back tasks. The orders of the trial blocks are selected randomly. Each trial block starts with 5 seconds of instruction. In each trial, 22 stimuli were presented to the participant where each stimulus was shown for 0.5 seconds followed by 1.5 seconds of a resting cross. Each trial block lasted a total of 49 seconds followed by a 10-second relaxation break where a resting cross is shown on the screen. After completing 8 trials, participants were given a 20 second relax break. At the end of each session, the participant was given a 2-minute relaxation break. During the experiment, the participant response and the reaction time corresponding to each stimulus were recorded. The physiological recordings includes functional near-infrared spectroscopy, electrodermal activity, electrocardiogram, photoplethysmogram, respiration, and skin temperature. A detailed description of the experiment is provided in [18].

B. State-Space Model for Performance

In this study, the observations related to performance include the participant responses corresponding to each stimulus (correct/incorrect responses) and the reaction time (the time taken to respond after a stimulus was shown). We consider the correct/incorrect responses as a set of binary observations. The experiment consists of k trials in which each trial has a continuous (reaction time) and a binary observation (correct/incorrect response). Let the continuous and binary observations be r_k and n_k, respectively for k^{th} $\forall k = 1, 2, \cdots, K$. We define an unobserved performance state process x_k which is related to the observation similar to [15]. We assume that the dynamics in the performance state follow the first-order process as follows,

$$x_k = \rho x_{k-1} + v_k \tag{1}$$

where $0 < \rho < 1$ is the state transition coefficient, and ν_k represents the process noise. We model ν_k as independent zero mean Gaussian random variables with variance σ_v^2 . x = $[x_0 \;\; x_1 \cdots x_k]$ represents the unobserved performance state for the whole study. The observation model for continuous measurements is

$$z_k = \log(r_k) = \alpha + \beta x_k + \epsilon_k \tag{2}$$

in which ϵ_k represents independent zero-mean Gaussian random variables with variance σ_ϵ^2. Z = $[z_0 \; z_1 \cdots z_k]$ represents the log of the reaction time. It is assumed that the observation model for the binary measurements is represented by the Bernoulli probability model

$$Pr(n_k|x_k) = p_k^{n_k}(1 - p_k)^{1-n_k} \tag{3}$$

where p_k is the probability of obtaining a correct response in trial k. p_k is represented by

$$p_k = \exp(\mu + x_k)[1 + \exp(\mu + x_k)]^{-1} \tag{4}$$

where p_k is represented in terms of the performance state process, ensuring that the probability of a correct response will lie between 0 and 1 and that as the performance state increases, the probability of obtaining a correct response approaches 1. Assuming there is no bias in the participant's response at the beginning of the experiment, the parameter μ is estimated from p_0 which is the probability by chance of a correct response at the beginning of the experiment. When executing the binary response task, it is assumed that p_0 is going to be 0.5 at the beginning of the experiment. When k = 0, $p_0 = 0.5$, and x_0 = 0, the parameter μ can be estimated by using equation 4: $\hat{\mu} = \log[(1-p_0)^{-1}p_0]$. After the performance states and the model parameters have been estimated from the data across the whole experiment, the estimate of x_0, i.e., $\hat{x}_0$ can potentially take on a value other than zero. In this scenario, p_0, the probability of obtaining a correct response at the beginning of the experiment, differs from chance and can be estimated utilizing equation 4: $p_0 = [1+\exp(\hat{\mu}+\hat{x}_0)]^{-1}\exp(\hat{\mu}+\hat{x}_0)$. Difference in p_0 and the probability by chance demonstrates that x_0 does not equal to 0 and that there is a bias in the participants response at the beginning of the experiment. N = $[n_0 \; n_1 \cdots n_k]$ represents the sequence of correct and incorrect responses on all k trials [15].

C. Estimation of the Reaction Time and Performance Curve

Since x is a hidden state and $\theta = (\rho, \alpha, \beta, \sigma_v^2, \sigma_\epsilon^2)$ is a set of unknown parameters, the EM algorithm is utilized to estimate these unknowns [15]. In each iterations of the

EM algorithm, the E-step consists of estimating the expected values of $x_k \forall k$ using the FIS algorithm [15]. We perform a Gaussian approximation for the observation equation to derive the steps of FIS algorithm similar to [15]. We denote these expected values as $x_{k|K}$ and $\sigma^2_{k|K}$, where the subscript denotes estimated expectation corresponds to k time point and based on all K observations. The *forward filter* equations of FIS are as follows,

Predict:

$$\begin{aligned} x_{k|k-1} &= \rho x_{k-1|k-1}, \\ \sigma^2_{k|k-1} &= \rho^2 \sigma^2_{k-1|k-1} + \sigma^2_\nu, \end{aligned} \tag{5}$$

Update:

$$x_{k|k} = x_{k|k-1} + \frac{\sigma^2_{k|k-1}}{\beta^2 \sigma^2_{k|k-1} + \sigma^2_\epsilon} \Big[\sigma^2_\epsilon (n_k - p_{k|k}) + \beta (I_k - \alpha - \beta x_{k|k-1}) \Big], \tag{6}$$

$$\sigma^2_{k|k} = \left[\frac{1}{\sigma^2_{k|k-1}} + p_{k|k}(1 - p_{k|k}) + \frac{\beta^2}{\sigma^2_\epsilon} \right]^{-1}. \tag{7}$$

The *Backward smoother* equations in FIS are,

$$A_k = \rho \frac{\sigma^2_{k|k}}{\sigma^2_{k+1|k}}, \tag{8}$$

$$x_{k|K} = x_{k|k} + A_k (x_{k+1|K} - x_{k+1|k}), \tag{9}$$

$$\sigma^2_{k|K} = \sigma^2_{k|k} + A_k^2 (\sigma^2_{k+1|K} - \sigma^2_{k+1|k}). \tag{10}$$

The following expectations are also estimated at the end of the expectation step,

$$E\{x_k^2\} = x^2_{k|K} + \sigma^2_{k|K}, \tag{11}$$

$$E\{x_{k+1} x_k\} = x_{k+1|K} x_{k|K} + A_k \sigma^2_{k+1|K}. \tag{12}$$

The M-step utilizes $x_{k|K}$ and $\sigma^2_{k|K}$ estimates to find θ by maximizing the expectation of the complete log-data likelihood. The expectation of log-data likelihood function Q is defined as

$$\begin{aligned} Q = &\sum_{k=1}^{K} E\{n_k(\mu + x_k) - \log(1 + \exp[\mu + x_k])\} \\ &+ \left(\frac{-K}{2}\right) \log(2\pi\sigma^2_\epsilon) - \sum_{k=1}^{K} \frac{E\left\{(z_k - \alpha - \beta x_k)^2\right\}}{2\sigma^2_\epsilon} \\ &+ \left(\frac{-K}{2}\right) \log(2\pi\sigma^2_\nu) - \sum_{k=1}^{K} \frac{E\left\{(x_k - x_{k-1})^2\right\}}{2\sigma^2_\nu}. \end{aligned} \tag{13}$$

The probability density of the estimate of the log reaction time at trial k can be calculated by utilizing (2), smoothing algorithm estimate of x_k, and the standard change-of-variables formula from the elementary probability theory. After implementing the change-of-variable formula to the equation $r_k = \exp(\alpha + \beta x_k)$ and the probability density that conditional on the data Z, N, and x_k has an approximate Gaussian probability density with mean $x_{k|K}$ and variance $\sigma_{k|K}$ gives us the log normal random variable r_k based on the data Z and N as follows [15],

$$f(r|\mu, x_{k|K}, \sigma^2_{k|K}) = \frac{1}{\sqrt{(2\pi\sigma^2_{k|K})}} \exp\left[-\frac{1}{2\sigma^2_{k|K}} \left(\frac{\log[r - \alpha]}{\beta} - x_{k|K} \right)^2 \right]. \tag{14}$$

The reaction-time curve is defined as the plot of $r_{k|K}$ versus k. Here $r_{k|K}$ is the mode of the density function, i.e., the location of the maximum value in the density function in (14). Similarly, the probability density of p_k based on the observation Z and N is obtained as follows [15],

$$f(p|\mu, xk|K, \sigma^2_{k|K}) = \frac{1}{p(1-p)\sqrt{2\pi\sigma^2_{k|K}}} \times \exp\left[-\frac{1}{2\sigma^2_{k|K}} (\log\left[\frac{p}{(1-p)\exp(\mu)}\right] - x_{k|K} - x_{k|K})^2 \right]. \tag{15}$$

The performance curve is defined as the plot of $p_{k|K}$ versus k, where $p_{k|K}$ is the mode of Eq. 15.

D. High Performance Index

Similar to [15] and [13], we define a metric called the high performance index (HPI), which is calculated by the probability that performance x_k exceeds a specific threshold, i.e.,

$$\text{HPI} = \Pr(x_k > x_T) \tag{16}$$

HPI represents how much a person's performance is above a certain baseline. To estimate this probability, we need the probability density function of x_k. The probability density function is defined as $x_k \sim \mathcal{N}(x_{k|K}, \sigma^2_{k|K})$ where $x_{k|K}$ and $\sigma^2_{k|K}$ are obtained after EM convergence. In this study, we calculate x_T by taking the mean of $x_{k|K}$.

III. Results and Discussion

The estimated mean reaction times for all participants are 480.42, 801.10, 437.61, and 680.99 seconds for 1-back calming, 3-back calming, 1-back vexing, and 3-back vexing, respectively. The corresponding standard deviations are 112.54, 159.59, 125.29, and 97.23 seconds, respectively. The corresponding estimated probabilities of the correct response for all participants are 0.8456, 0.6108, 0.8532, and 0.6723, respectively.

We successfully utilize the binary response observations n_k (i.e. correct/incorrect response) and the corresponding reaction times r_k for $\forall k$ to estimate the performance $x_{k|K}$ using the proposed model and the EM approach. Figure 1 shows an example of the the performance state estimation result. The figure illustrates the estimated distribution of r_k, x_k, and p_k. The final sub-panel provides the estimated HPI calculated using equation 16.

We investigate how the HPI changes from one task to another task during different types of music. Figure 2 represents the estimated average of the HPI for four different transitions during calming music and three different transitions during vexing music. We observe from visual inspection that the HPI does not change significantly during the transition

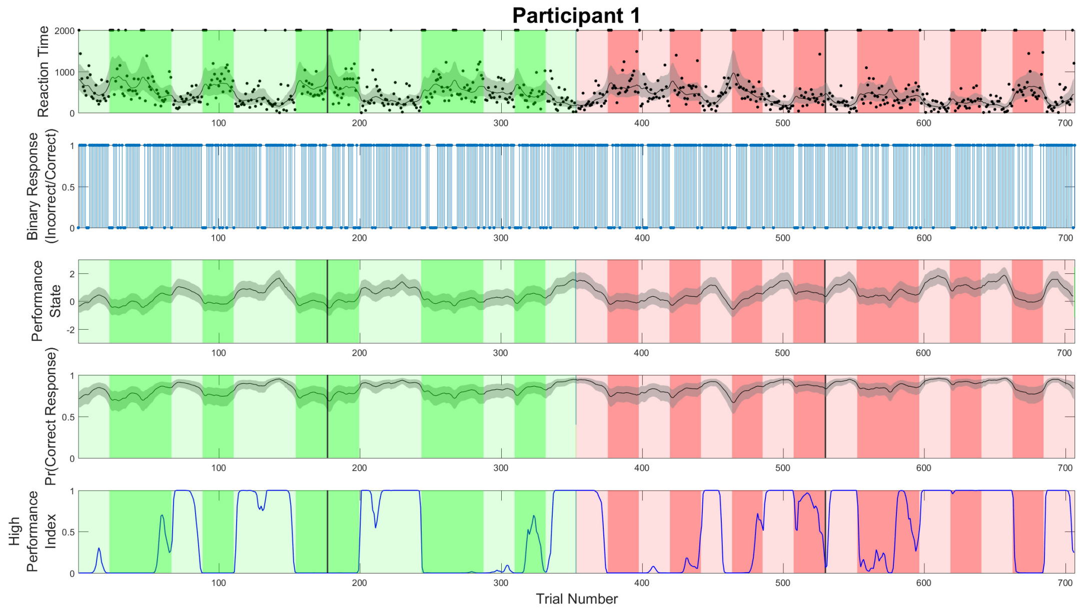

Fig. 1: **Performance State Esitmation for One Participant.** The top sub-panel shows the measured reaction time (black dots), reconstructed reaction time (black) along with the 95% confidence interval. The second sub-panel shows the correct incorrect responses. Third and fourth sub-panels illustrate the estimated performance state (black curve) and the probability of the correct and incorrect responses (black curve) along with their 95% confidence interval (gray shade). The last sub-panel shows the HPI (blue curve). The red and green background colors correspond to the calming and vexing music trials, respectively. The lighter background color corresponds to 1-back tasks and darker color corresponds to 3-back tasks.

between similar types of tasks for all six participants. On the other hand, the transition between different types of tasks shows changes in HPI. For all participants, an increase in performance is observed for the case of switching from the 3-back to the 1-back task. The opposite is observed while switching between the 1-back to the 3-back task. This pattern is especially consistent during the calming music period. This resembles our previous understanding that the 1-back task is easier than the 3-back task. During the vexing music, the differences between the 1-back task and the 3-back tasks seem visually less different than those of the calming music, which could be an indication that during the vexing music the participant is performing better during the 3-back task.

We further calculate the average of the estimated performance states during each of the trial blocks to compare the averages among different tasks in the presence of different types of music. Figure 3 shows the distributions of the estimated averages. From visual inspection, we observe that for all participants, the mean of the distribution of the average performance states increases during the vexing music. We perform statistical tests between these distributions for each of the participants individually to determine whether the difference in the average performance during two different music stimulations is statistically significant or not. We perform a two-sample pooled t-test between the average performances during the two types of music for both 1-back task and 3-back tasks. Our analysis shows that only Participant 3 showed a significant difference between 1-back calming and 1-back vexing ($p < 0.05$). The differences for all other participants were statistically insignificant. Therefore, no difference is seen during 1-back tasks while listening to two different types of music. On the other hand, a significant difference between 3-back calming and 3-back vexing were observed ($p < 0.05$) for all six participants.

As observed from the statistical analysis, the change of music from calming to vexing has more effect on the 3-back task, which is the harder one among the two tasks. From the HPI estimation, the performance is low usually during 3-back task while listening to calming music. From the investigation during 3-back tasks, we see that the participants tend to perform better while listening to the vexing music. Perhaps, the vexing nature of the music was helping the participants to concentrate better. However, this could not be seen during the 1-back task. One possible explanation is that the performance matrices of the participants are already very high, i.e., HPI is greater than 0.5 for most of the cases, during the 1-back task while listening to calming music as the task is relatively easy to perform. Therefore, the performance state remained almost unchanged during both types of music. This finding based on this experiment revealed that music might have a profound effect on the higher-level cognitive load. Our results conforms with the findings in [2]. According to this [2], tasks that pose a small burden on working memory are not influenced by background music and the tasks that pose a high burden on working memory are influenced by background music.

It might seem counter-intuitive that the vexing music is helping the participants to have the higher level of performance. One possible explanation is that the n-back task is very repetitive and can cause boredom and the vexing music is keeping the participants more engaged in the task compared to the calming one. The result might change in the

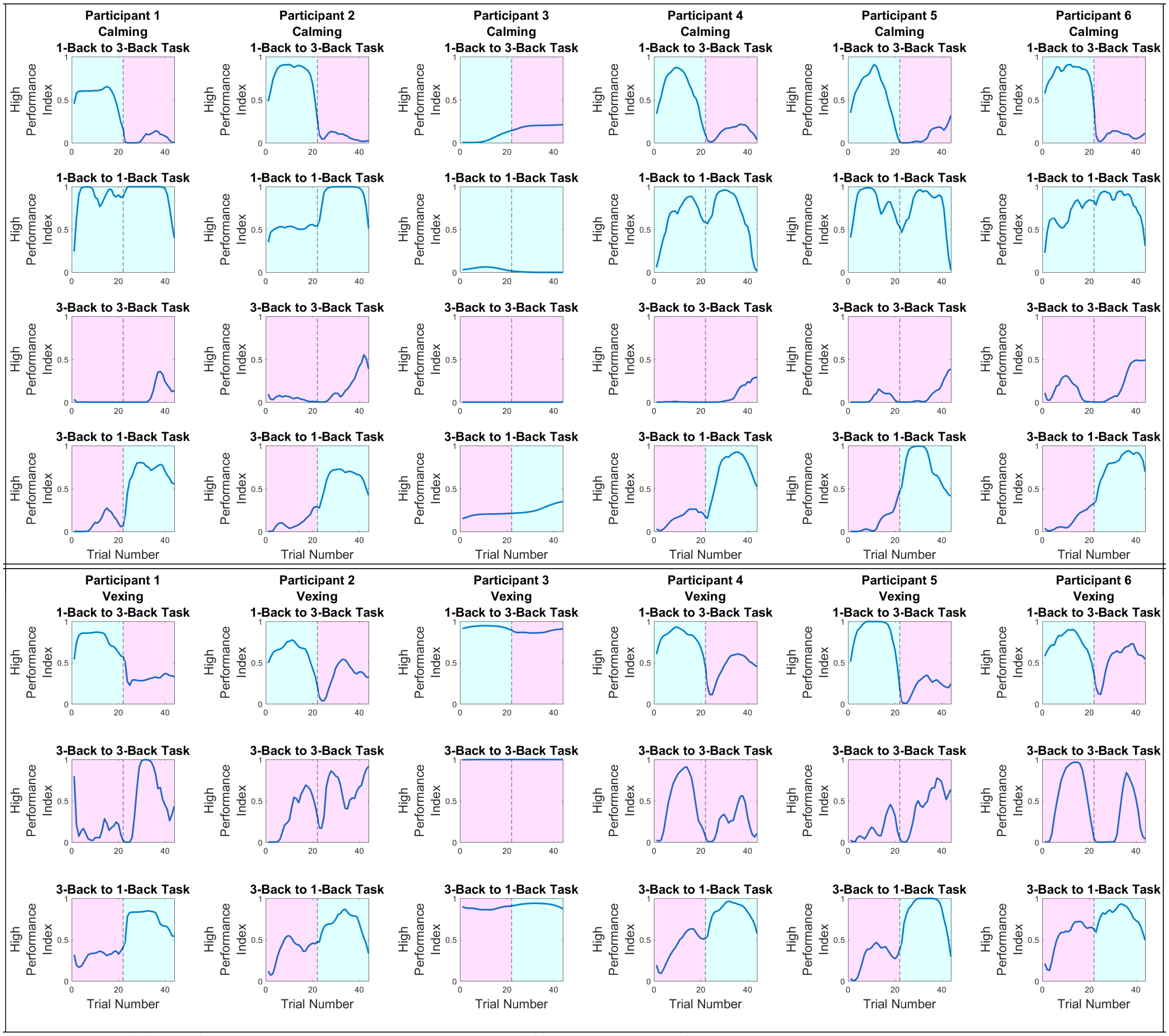

Fig. 2: **Transition of High Arousal Index between Different Types of Tasks.** The top sub-figure shows how the average HPI changes from one type of task to another type of task during calming music for six participants. Similarly, the bottom sub-figure shows how the average HPI changes from one type of task to anther type of task during vexing music. The cyan and pink backgrounds correspond to 1-Back and 3-Back Task

case of a different type of task.

IV. Conclusion

Stress can heavily impact individual performance if not properly regulated. In this study, we investigate how different types of music influence individual performance during a WM cognitive task. We propose to utilize a state-space approach to investigate individual performance. We successfully obtain the performance states and performance indices from the binary correct/incorrect response and the corresponding reaction time from the participants. We perform a rigorous visual inspection followed by statistical analysis. Our investigation concludes that the participants have shown to have higher levels of performance while listening to their choice of vexing music.

The study has a significant impact on designing closed-loop systems for controlling individual stress levels using non-invasive actuators for maximizing performance and productivity [19]. We plan to utilize physiological measurements to estimate the matrices for quantifying the stress similar to the approach in [13], [20]–[22] and use it to infer the effect of different types of actuation such as music for designing appropriate closed-loop cyber-physical systems.

Acknowledgment

The authors thank Dilranjan S. Wickramasurya and Srinidhi Parshi for their help during data collection and preparation of the dataset.

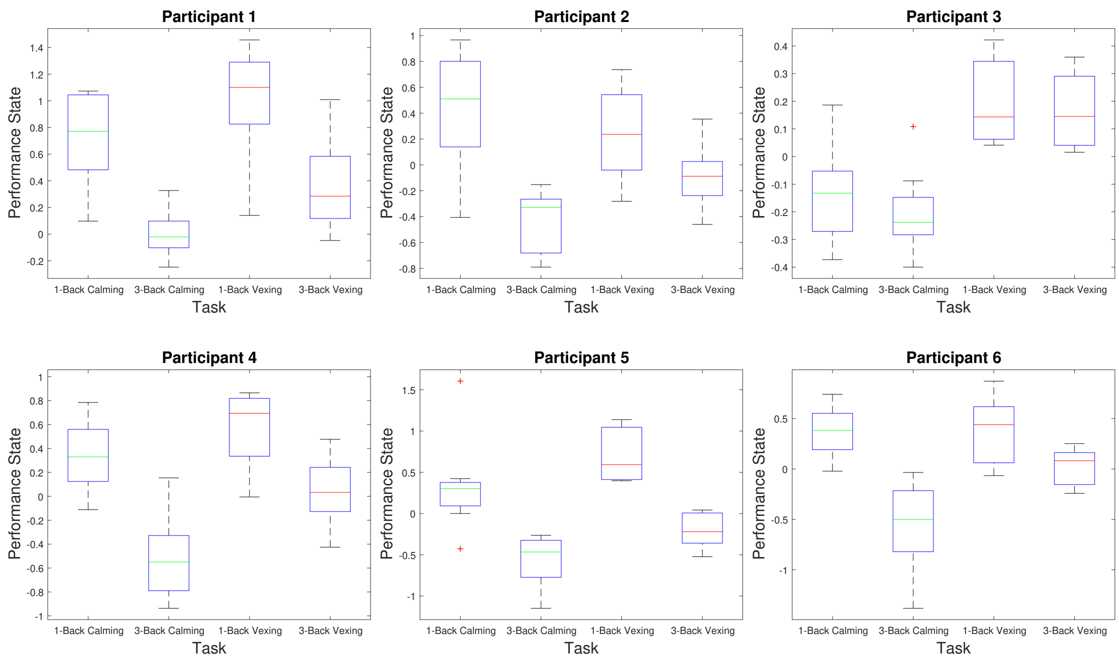

Fig. 3: **Distribution of Performance States During Different Tasks and Music.** Each sub-figure shows that the box-plot illustrating the distribution of the estimated performance states for each participant while performing two types of n-back tasks in presences calming and vexing music.

References

[1] A. J. Tomiyama, "Stress and obesity," *Annual review of psychology*, vol. 70, pp. 703–718, 2019.

[2] J. A. Lehmann and T. Seufert, "The influence of background music on learning in the light of different theoretical perspectives and the role of working memory capacity," *Frontiers in psychology*, vol. 8, p. 1902, 2017.

[3] K. Khaksari, E. Condy, J. B. Millerhagen, A. A. Anderson, H. Dashtestani, and A. H. Gandjbakhche, "Effects of performance and task duration on mental workload during working memory task," in *Photonics*, vol. 6, p. 94, Multidisciplinary Digital Publishing Institute, 2019.

[4] M. Nithya.S, "Analysis of music effect on n-back task performance," pp. 38–42, 2016.

[5] Y. Jing, S. Jing, C. Huajian, S. Chuangang, and L. Yan, "The gender difference in distraction of background music and noise on the cognitive task performance," in *2012 8th International Conference on Natural Computation*, pp. 584–587, IEEE, 2012.

[6] D. S. Wickramasuriya and R. T. Faghih, "A mixed filter algorithm for sympathetic arousal tracking from skin conductance and heart rate measurements in pavlovian fear conditioning," *PloS one*, vol. 15, no. 4, p. e0231659, 2020.

[7] D. S. Wickramasuriya and R. T. Faghih, "A marked point process filtering approach for tracking sympathetic arousal from skin conductance," *IEEE Access*, vol. 8, pp. 68499–68513, 2020.

[8] T. Yadav, M. M. U. Atique, H. F. Azgomi, J. T. Francis, and R. T. Faghih, "Emotional valence tracking and classification via state-space analysis of facial electromyography," in *2019 53rd Asilomar Conference on Signals, Systems, and Computers*, pp. 2116–2120, IEEE, 2019.

[9] M. B. Ahmadi, A. Craik, H. F. Azgomi, J. T. Francis, J. L. Contreras-Vidal, and R. T. Faghih, "Real-time seizure state tracking using two channels: A mixed-filter approach," in *2019 53rd Asilomar Conference on Signals, Systems, and Computers*, pp. 2033–2039, IEEE, 2019.

[10] D. S. Wickramasuriya and R. T. Faghih, "A bayesian filtering approach for tracking arousal from binary and continuous skin conductance features," *IEEE Transactions on Biomedical Engineering*, vol. 67, no. 6, pp. 1749–1760, 2019.

[11] D. S. Wickramasuriya and R. T. Faghih, "A cortisol-based energy decoder for investigation of fatigue in hypercortisolism," in *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 11–14, IEEE, 2019.

[12] D. S. Wickramasuriya and R. T. Faghih, "A novel filter for tracking real-world cognitive stress using multi-time-scale point process observations," in *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 599–602, IEEE, 2019.

[13] D. S. Wickramasuriya, M. Amin, R. T. Faghih, *et al.*, "Skin conductance as a viable alternative for closing the deep brain stimulation loop in neuropsychiatric disorders," *Frontiers in neuroscience*, vol. 13, p. 780, 2019.

[14] D. S. Wickramasuriya, C. Qi, and R. T. Faghih, "A state-space approach for detecting stress from electrodermal activity," in *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 3562–3567, IEEE, 2018.

[15] M. J. Prerau, A. C. Smith, U. T. Eden, Y. Kubota, M. Yanike, W. Suzuki, A. M. Graybiel, and E. N. Brown, "Characterizing learning by simultaneous analysis of continuous and binary measures of performance," *Journal of neurophysiology*, vol. 102, no. 5, pp. 3060–3072, 2009.

[16] S. Parshi, R. Amin, H. F. Azgomi, and R. T. Faghih, "Mental workload classification via hierarchical latent dictionary learning: A functional near infrared spectroscopy study," in *2019 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI)*, pp. 1–4, IEEE, 2019.

[17] C. Coulacoglou and D. Saklofske, "Chapter 5-executive function, theory of mind, and adaptive behavior," *C. Coulacoglou & DH Saklofske (Éd.), Psychometrics and Psychological Assessment*, pp. 91–130, 2017.

[18] S. Parshi, "A functional-near infrared spectroscopy investigation of mental workload," Master's thesis, University of Houston, 2020.

[19] H. Fekri Azgomi, D. S. Wickramasuriya, and R. T. Faghih, "State-space modeling and fuzzy feedback control of cognitive stress," in *Annual International Conference of the Engineering in Medicine and Biology Society*, July 2019.

[20] M. R. Amin and R. T. Faghih, "Inferring autonomic nervous system stimulation from hand and foot skin conductance measurements," in *52th Asilomar Conference on Signals, Systems and Computers*, 2018.

[21] M. R. Amin and R. T. Faghih, "Robust inference of autonomic nervous system activation using skin conductance measurements: A multi-channel sparse system identification approach," *IEEE Access*, vol. 7, pp. 173419–173437, 2019.

[22] M. R. Amin and R. T. Faghih, "Sparse deconvolution of electrodermal activity via continuous-time system identification," *IEEE Transactions on Biomedical Engineering*, vol. 66, no. 9, pp. 2585–2595, 2019.