# Wearable-Machine Interface Architectures for Mental Stress

Md. Rafiul Amin, Dilranjan S. Wickramasuriya, Student Member, IEEE, Rose T. Faghih, Member, IEEE

Abstract—The human body responds to neurocognitive stress in multiple ways through its autonomic nervous system. Changes in skin conductance measurements indicate sudomotor nerve activity, and can be used to infer the underlying autonomic nervous system stimulation. We model skin conductance measurements using a state-space model with sparse impulsive events as inputs. Next, we recover the timing and amplitudes of this spiking neural activity using a generalized cross-validation based sparse recovery approach. Finally, we relate stress to the probability that a neural spike occurs in a skin conductance signal to continuously track a subject's stress level. Results demonstrate a promising approach for tracking stress through wearable devices.

### I. Introduction

Variations in human emotion can be accounted for along two different dimensions—valence, denoting the pleasure—displeasure axis, and arousal, denoting activation or excitement. Stress involves high arousal, unpleasantness and a loss of control. The relationship between arousal and skin conductance has been attested to in multiple studies [1]. We present a mechanism for recovering the underlying neural stimuli leading to sweat gland secretions (which cause changes in skin conductance) and a state-space model for detecting stress based on the frequency of this neural spiking activity.

II. METHODS

# A. Sparse Neural Stimuli Recovery

The phasic component in skin conductance data, which is known to be the smoothed version of underlying sparse neural spiking activity, can be extracted using cvxEDA [2]. Using a state-space model of the smoothing system based on the physiology of sweat secretion and evaporation, we formulate an optimization problem to recover the sparse stimuli and estimate model parameters. This optimization problem is divided into two sub-problems having two different sets of physiological constraints and is solved iteratively until convergence. We solve the sparse recovery problem with the GCV-FOCUSS+ algorithm [3] and estimate model parameters using the interior-point method similar to [3]. Then, the recovered sparse stimuli are converted to binary sequences.

Md. Rafiul Amin, Dilranjan S. Wickramasuriya, and Rose T. Faghih are with the Department of Electrical and Computer Engineering at the University of Houston, Houston, TX 77004 USA (e-mail:{mamin, dswickramasuriya, rtfaghih}@uh.edu). This work was supported in part by NSF grant 1755780. Correspondence should be addressed to senior author Rose T. Faghih.

### B. Stress State Estimation

We use Expectation-Maximization (EM) for estimating stress [1]. We first assume the brain's stress state follows a random walk with time. The higher a person's arousal or stress level, the more frequent the neural spiking. Therefore, we relate stress to the probability that a neural spike occurs through a sigmoid function. We next use a Gaussian approximation, and forward and backward Kalman-like filter equations. We alternate between E-step filter equations and M-step parameter updates until convergence. Stress is finally expressed within a [0, 1] interval based on an ideal's observer's certainty level.

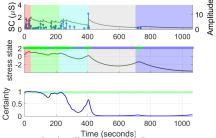


Fig. 1. Sparse neural stimuli recovery and stress state estimation The first panel shows a skin conductance signal and its recovered neural stimuli; the bottom two panels depict the corresponding stress state estimate and the ideal's observer certainty level. The first three background shades (red, green and cyan) on the left correspond to different cognitive stress periods. The next two shades (grey and blue) depict relaxation and a horror movie respectively.

III. RESULTS

Fig. 1 shows the neural stimuli recovered from a skin conductance signal in [4] and the corresponding stress estimate.

IV. CONCLUSION

Here, we present a method for recovering neural stimuli from skin conductance using compressed sensing, and an EM approach for estimating stress from that neural activity.

## REFERENCES

- D. S. Wickramasuriya, C. Qi, and R. T. Faghih, "A state-space approach for detecting stress from electrodermal activity," in *Proc. 40th Annu. Int. Conf. IEEE Eng. in Medicine and Biology Society*, IEEE, 2018.
- [2] A. Greco, G. Valenza, A. Lanata, E. P. Scilingo, and L. Citi, "cvxeda: A convex optimization approach to electrodermal activity processing," *IEEE Trans Biomed. Eng.*, vol. 63, no. 4, pp. 797–804, 2016.
- [3] R. T. Faghih, M. A. Dahleh, G. K. Adler, E. B. Klerman, and E. N. Brown, "Deconvolution of serum cortisol levels by using compressed sensing," *PloS one*, vol. 9, no. 1, p. e85204, 2014.
- [4] D. C. M. B. P. Birjandtalab, Javad and M. Nourani, "A non-EEG biosignals dataset for assessment and visualization of neurological status," in *IEEE Int. Workshop Signal Process. Syst. (SiPS)*, pp. 110– 114, 2016.