

# A Mixed-Filter Algorithm for Arousal Tracking from Galvanic Skin Response and Heart Rate Measurements

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**Abstract**—Variations in physiological signals accompany different types of emotions. In particular, changes in skin conductance and heart rate—being under the control of the autonomic nervous system—can be observed during feelings of excitement, fear and stress. We design a mixed-filter algorithm for tracking arousal from skin conductance and heart rate measurements. We relate the brain’s unobserved arousal state to a subject’s heart rate and to three skin conductance measures. We use Expectation–Maximization for state estimation and model parameter recovery.

**Index Terms**—skin conductance, heart rate, state estimation

## I. INTRODUCTION

Human emotion can be accounted for along two major axes—arousal and valence. Arousal denotes the activation or excitement accompanying an emotion. These emotional changes manifest themselves through different physiological signals such as skin conductance, electrocardiography and electroencephalography. Many of these signals can be analyzed from a point process framework. We present a mixed filter algorithm inspired by the point process method in [1] for tracking arousal from skin conductance and heart rate.

## II. METHODS

We relate three skin conductance features (the occurrence of skin conductance response (SCR) peaks, the amplitude of these peaks and the tonic skin conductance level) [2] and heart rate to an arousal state  $X_k$  that is assumed to follow a first-order autoregressive model with time. We model heart beat inter-arrival times using a history-dependent inverse Gaussian (HDIG) probability density function [3]. We take the HDIG mean value to be a weighted sum of previous RR-intervals and  $X_k$ . Expectation-Maximization (EM) is used for state estimation and model parameter recovery. In the E-step, we use a Gaussian approximation to derive the forward filter and backward smoother equations. Parameters maximizing the complete data log likelihood are chosen at the M-step and the algorithm iterates between the steps until convergence.

## III. RESULTS AND CONCLUSION

We evaluate our model on a fear conditioning task [4] with red and blue rectangles as the conditioned stimuli (CS+ and CS-) and electric shocks as the unconditioned stimuli. Prior studies in fear conditioning have noted that the CS+ trials give rise to the highest skin conductance responses in comparison

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to the CS- trials. Our results (Fig. 1) are in close agreement with this. The brain’s arousal state is highest in trials where the electric shock is given and is lower in the other trials. Thus, a mixed filter based on skin conductance and heart rate measurements is a promising unsupervised approach for estimating a continuous-valued arousal level.

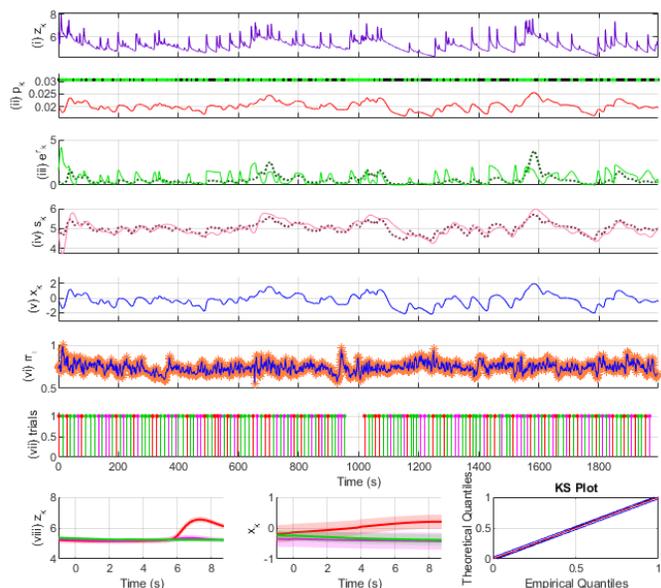


Fig. 1. **Tracking arousal in fear conditioning.** The sub-panels depict, (i) skin conductance; (ii) SCR peak occurrence probabilities; (iii), (iv) fits to two continuous-valued measures (the phasic-derived peak amplitudes envelope and the tonic baseline respectively); (v) the arousal state  $X_k$ ; (vi) fits to RR-intervals; (vii) red, mauve and green for the CS+ trials containing the shock, CS+ without the shock and CS- respectively; (viii - left) trial-averaged skin conductance responses; (viii - middle) trial-averaged arousal states; (viii - right) KS plot for the heart rate using its conditional intensity function; the plot falls within the 95% confidence limits.

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