TOWARDS AMBULATORY EMOTION RECOGNITION

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I. INTRODUCTION

Emotion recognition through physiological recording is an emerging field of research with many promising results stemming from laboratory control studies. The aim is to identify potential patterns in autonomic activity, indexed by features like heart and respiration rate, which are specific to the basic emotions (i.e. fear, disgust, sadness, anger and happiness) [1]. A common experiment paradigm is to employ non-invasive, surface sensors to record physiological responses of subjects presented with emotionally evocative stimuli [2]. Previous studies have conducted such experiments using stimuli in the form of film clips [3], pictures [4] and personal imagery [5].

Physiological response pattern analyses that have been explored in emotion recognition include linear discriminants, Mahalanobis distance classifiers, support vector machines, cluster analysis and classifier ensembles [2,4,5]. Classification accuracies have been reported to range from 60 to 90% depending on the classifier used and the individual [2,3,4]. However, many of these techniques are supervised and require *a priori* knowledge of which segments of signal are associated with baseline or emotional response. Practical applications would ideally adopt an approach more akin to sequential (online) change or trend detection [6].

Singular spectrum analysis (SSA) is a relatively new method capable of online change point analysis that does not assume prior structure of the data (e.g. normality, an assumption that is common in many change point algorithms and one that is rarely met by physiological data). The algorithm works by finding underlying structures in observed data and announces a change when incoming data no longer fit that structure. In this paper, we implement a version of SSA for exploratory analysis of change points that may be present during baseline-to-stimulus transitions in physiological signals with the aim of determining the differences of these states between sitting and walking conditions.

The remainder of this paper is outlined as follows. Section II will give a brief description of the SSA algorithm. Section III describes the instrumentation and methodology employed to gather physiological data from participants. Section IV describes our methods of analysis and section V exhibits some results obtained from SSA with some interpretations.

II. SINGULAR SPECTRUM ANALYSIS

Here we provide a brief description of the SSA algorithm according to [7]. For a more detailed treatment on the subject, see [8].

Given a time series $x_t = \{x_1, x_2, \ldots x_T\}$, where the subscripts are time indices, The algorithm follows these steps for each possible point in the time series:

1) Construct L-dimensional subspace

Construct the trajectory matrix:

$$H(t) = \begin{bmatrix} x_{t+1} & x_{t+2} & \cdots & x_{t+K} \\ x_{t+2} & x_{t+3} & \cdots & x_{t+K+1} \\ x_{t+3} & & \ddots & \vdots \\ \vdots & \vdots & & \vdots \\ x_{t+M} & x_{t+M+1} & \cdots & x_{t+N} \end{bmatrix}$$

Where N is the window length, M is the lag parameter (set to $\lfloor N/2 \rfloor$ by [7]) and K = N-M+1 by definition. Note that H is a Hankel matrix where elements in the skew-diagonals are equal. The next step is to decompose the lag-covariance matrix HH^T using singular value decomposition giving M eigenvectors. Select a

group L, which is a subset of *l* < M eigenvectors to represent a subspace in $\Re^M$.

2) Construct Test Matrix

The test matrix is constructed similarly to the trajectory matrix:

$$X_{test}(t) = \begin{bmatrix} x_{t+p+1} & x_{t+p+2} & \cdots & x_{t+q} \\ x_{t+p+2} & x_{t+p+3} & \cdots & x_{t+q+1} \\ x_{t+p+3} & & \ddots & \vdots \\ \vdots & \vdots & & \vdots \\ x_{t+p+M} & x_{t+p+M+1} & \cdots & x_{t+q+M-1} \end{bmatrix}$$

Where the parameters p and q determine the amount of overlap with the trajectory matrix and how far ahead you want to detect changes in the time series.

Calculate distance statistic

The distance between a column X_j in X_{test} and the *l*-dimensional subspace defined by the group L is computed as:

$$D = \left\| X_j \right\|^2 - \left\| L^T X_j \right\|^2 = X_j{}^T (I_M - LL^T) X_j$$

Where I_M is the MxM identity matrix. The distance statistic at the point t is then calculated as:

$$D_{L,p,q}(t) = \sum_{j=p+1}^{q} X_j{}^{(t)^T} (I_M - LL^T) X_j{}^{(t)}$$

[7] suggests normalizing this distance statistic as:

$$S(t) = \frac{1}{MQ} \frac{D_{L,p,q}(t)}{D_{L,0,K}(t)}$$

A CUSUM-type statistic is then calculated as:

$$W(1) = S(1)$$

$$W(t) = [W(t-1) + S(t) - S(t-1) - \kappa / \sqrt{MQ}]^+$$

Where $[a]^+$ refers to max{0,a} and κ is a small nonnegative constant set to $1/(3\sqrt{MQ})$ by [7]. The statistic W is then compared to a threshold:

$$h = \frac{2Z_\alpha}{MQ} \sqrt{\frac{1}{3} Q(3MQ - Q^2 + 1)}$$

Where Z_α is the (1-α) quantile of the standard normal distribution. Change points are announced when W exceeds this threshold.

Variants of the SSA algorithm described above exist (See [9] as an example). We applied this SSA algorithm to features extracted from physiological recordings of subjects that were either sitting or walking during baseline and stimulus presentation periods for exploratory change-point analysis.

III. METHODOLOGY

Instrumentation

We recorded electrocardiogram (ECG), skin conductance and respiratory activity using Thought Technology's (Montreal, Quebec, Canada) Procomp set of physiological sensors. The ECG was recorded using the three-lead configuration (Einthoven's triangle) using disposable Ag/AgCl gel electrodes. Skin conductance was recorded from the middle phalange of the second and third digits of the non-dominant hand. Respiratory activity was measured using strain gauge belts worn around the thorax and abdomen. All signals were sampled at 256Hz.

Participants Information

Fourteen subjects (7 males) between 18-27 years of age (mean=23, std=2.48) were recruited to participate in the experiment. All subjects had no known cardiovascular or psychiatric illnesses. Each subject was instructed to abstain from caffeine and other stimulants 24 hours prior to the experiment date and to wear shoes suitable for walking on a treadmill. Upon arrival to the experiment facility, subjects were re-briefed about the purpose of the study and the sequence of events in the experiment. Consent was obtained after addressing any questions the subject may have had. This study was reviewed and granted ethical approval by the Bloorview Research Ethics Board.

Experiment Protocol

After obtaining consent, the physiological sensors were attached to the subject followed

by measuring the subject's preferred walking speed on the treadmill using a method similar to that described in [10]. The subject was then given a trial run of the experiment stimulus presentation application (a custom program written in Visual Basic) and an explanation of the Self-Assessment Manikin for rating the stimulus items. Emotional stimuli were drawn from the International Affective Pictures System (IAPS) and the International Affective Digitized Sounds (IADS) libraries to allow comparison of ratings of items to nominal scores

The main experiment consisted of four randomized blocks – the result of a 2x2 factor crossing of mobility state (sitting vs. walking) and stimulus modality (visual vs. auditory). Each block began with a three-minute baseline segment followed by twenty cycles of stimulus presentation. Each cycle consisted of a randomized stimulus item presented for 8 seconds followed by an untimed subject rating section using the SAM and discrete emotion scores and ended with another 40-second baseline to allow physiological signals to settle before the next stimulus. Figure 1 contains a summary of the sequence of events in each experiment block.

IV. ANALYSIS

Signal Filtering and Feature Extraction

RR intervals were extracted from the ECG signal using a modified version of Pan and Thompkin's QRS detection algorithm [11]. Briefly, the ECG is band-passed, differentiated and squared before applying a moving integrator to produce another signal with peak locations corresponding to QRS complexes. An adaptive threshold is then applied to these peaks to specifically locate QRS complexes.

Respiration and skin conductance signals were low-pass filtered using a 4^{th} order Chebyshev Type II digital filter with cut-off frequency of 4Hz and 1Hz respectively and a ripple factor of 20dB. A peak detection algorithm based on detecting zero crossings of an approximate derivative signal was used to determine inspiration/expiration times and amplitudes in the respiratory signal. Skin conductance responses were detected with the same peak detection algorithm.

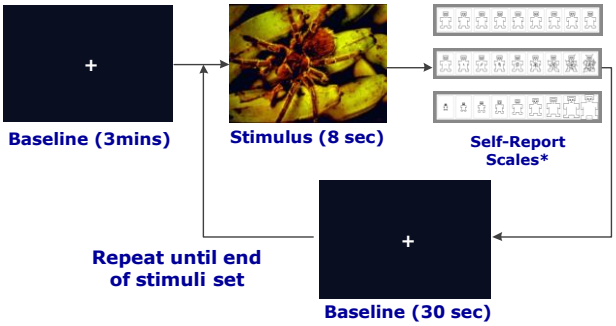

Figure 1: Sequence of events for one block of the experiment. *Self-Assessment Manikin and discrete emotion rating scales

SSA was applied to the time series of RR intervals, inspiration/expiration times with parameters N = 32, M = N/2, p = K+1, q = K+5. Parameters were chosen based on the knowledge of the cyclic behavior of heart rate with respiration rate. The change in trend of features was calculated as the difference in linear slope in M-point regions before and after a detected change point.

Data from four participants were excluded due to recording problems during the experiment. The Digital filtering, feature extraction and SSA change-point detection were implemented using MATLAB R2010a

V. RESULTS AND DISCUSSION

SSA Change Points

Due to space limitations, only RR-interval feature data will be reported here. Our exploratory SSA suggests that baseline conditions are non-stationary (See Figure 2 for an example of the aforementioned oscillatory structure of heart rate). Change point structure was also found to be subject-dependent, possibly due to varying levels of attention during the baseline segments or innate physiological differences. Table 1 contains the results of the trend analysis for RR-intervals showing differences in trend changes across change points between baseline and stimuli segments. The primary observation is the predominant negative sign in the change of RR-interval slope across change points suggesting the general change is an increase in heart rate during such events. The paired T-statistic for the difference in the amount of slope change between baseline and stimulus is significant at the 5% level but we are hesitant to draw

conclusions because the number of change points in each is grossly unbalanced due to the timing of the respective segments.

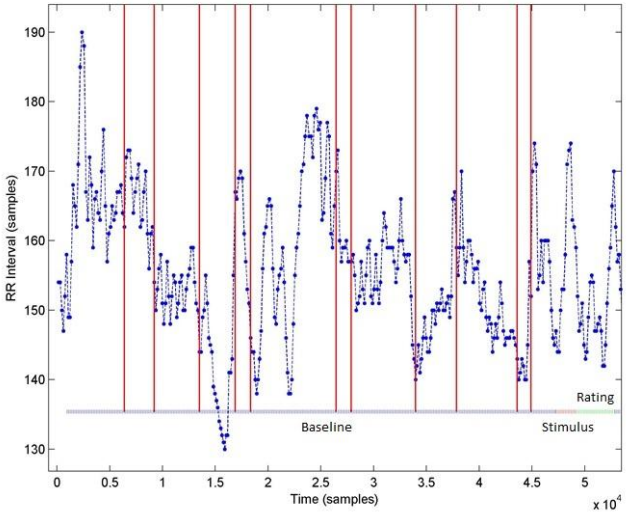

Figure 2: RR-interval change points (vertical red lines) found in a baseline segment suggesting non-stationarity.

Table 1: Slope changes of RR-interval series across change points by subject for sitting data. Values in table are: mean of slope change (# of change points in mean)

Subject	Change Point Location	
	Baseline	***Stimulus***
1	-7.8×10^{-4} (142)	-7.7×10^{-4} (32)
2	0.0037 (89)	-0.0077 (21)
3	-0.0021 (87)	-0.0071 (17)
4	0.0022 (55)	8.8×10^{-4} (17)
5	-0.0167 (76)	-0.0221 (25)
6	-0.002 (59)	-0.0047 (14)
7	-0.0051 (35)	-0.0179 (6)
8	0.0049 (92)	-0.0098 (16)
9	0.0069 (74)	-0.0021 (17)
10	-5.0×10^{-4} (81)	-0.0047 (11)
Total	-0.001 (790)	-0.0076 (176)

However, this analysis shows the potential of the application of SSA to detect trend changes in physiological data.

Noise Filtering

The quality of the feature time series depends heavily on noise rejection. We used digital filtering to reject noise (like most online systems) but SSA can also be applied to filtering. For example, [12] applied SSA on kinematic signals and demonstrated (visually) smoother results than with conventional digital filtering.

CONCLUSION

We explored the utility of SSA on physiological signals to detect change points in a baseline-vs-stimulus protocol and preliminary results suggest baseline feature data contain non-stationary structure that will need further characterization.

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