Physiological Correlates of Emotional State

Andrea K. Webb, Meredith G. Cunha, S.R. Prakash, and John M. Irvine

Charles S. Draper Laboratory,
555 Technology Square, Cambridge, Massachusetts, USA
{awebb,mcunha,sprakash,jirvine}@draper.com

Abstract. This study examined the relationship between emotion and physiological measures of autonomic system response. Features of electrodermal, cardiac, respiratory, movement, and oculomotor response were measured from a population of normal subjects while they were presented standard acoustic and visual stimuli designed to evoke specific emotions. The subjects' assessments of their emotional response to the stimuli (self-report) were also recorded. We present results of a preliminary analysis of the statistical relationship between the stimulus category, the physiological features and self-report. We found significant differences across stimulus categories, as well as across self-reported emotions, suggesting that a combination of features could be used to classify the emotional content of a discrete stimulus. We also examine the dependence of physiological signals on the mode of stimulus presentations.

Keywords: Affect, emotion, psychophysiology.

1 Introduction

The emotional state has an important influence on an individual's cognitive and behavioral response to external events. As a result, there is increasing interest in the emotional component of social (Parkinson, 1996) and human-computer interactions (reviewed in (Brave & Nass, 2002)). An individual's emotional state, however, remains inaccessible to direct measurement and manipulation. A number of studies have examined the question of indirectly assessing the emotional state by measuring observable correlates of emotion (Cowie, et al., 2001): facial expressions (Fasel & Luettin, 2003; Pantic & Rothkrantz, 2000), gestures (Mitra & Acharya, 2007) and gait (Karg, Kuhnlenz, & Buss), speech and voice patterns (Murray & Arnott, 1993), self-reports of the subjects experiencing the emotion, and physiological signals. Of these measures, physiology is least amenable to being influenced by voluntary action on part of the subject, and is therefore a promising indicator of the "true" emotional state. However, the mechanisms relating emotion and its physiological correlates, particularly the autonomic nervous system are poorly understood, subject to a number of confounding non-emotional influences, and to large inter-individual variation. As a result, few human-computer interface systems incorporate physiological measurements to assess affective state.

C. Stephanidis (Ed.): Posters, Part I, HCII 2011, CCIS 173, pp. 332–336, 2011.

In this study, we examine the relationship between physiological measurements and emotional state in a population of normal subjects presented standard affective stimuli. Prior work has found that there are differences in physiological responding when looking at pictures (Lang, Greenwald, Bradley, & Hamm, 1993) and for positive and negative emotions during directed facial action tasks (Ekman, Levenson, & Friesen, 1983; Levenson, Ekman, & Friesen, 1990). Prior work, however, typically has not looked at multiple stimulus modalities or included a broad array of physiological sensors. Our aim was to expand upon previous work by including a greater variety of physiological sensors and multiple emotion elicitation modalities.

2 Methods

32 participants (ages 19-55, 53% male, 47% female) were recruited from among employees of the laboratory. Informed consent was obtained, and the protocol approved by the New England Institutional Review Board.

Respiration and electrocardiogram (ECG) were collected with a Vivometrics Lifeshirt. Skin conductance (SC), finger pulse activity (FP), and gross body movement were collected with a Lafayette LX4000 polygraph. Pupil diameter and eye movement information were collected with a Tobii X50 eye tracker.

Emotionally evocative images and sounds were selected from the International Affective Picture System (Lang, et al., 1993) and International Affective Digital Sounds System (Bradley & Lang, 1999), respectively. Four stimuli for each emotion category and 4 neutral stimuli were selected, resulting in a total of 24 images and 24 sounds. E-Prime (Psychology Software Tools, Pittsburgh, PA) was used to control stimulus presentation. Each stimulus was presented for 6 seconds. Participants were then given 15 seconds to rate on a 7-point Likert scale (1=not at all, 7=a great amount) how much they felt of each of happiness, sadness, anger, fear, and disgust. For the mental imagery portion, participants were asked to remember for a 30-second period a specific personal event in which they felt the specified emotion. Participants then provided self-report ratings for how much they felt of each emotion.

CPSLAB (Scientific Assessment Technologies, Salt Lake City, UT) was used to remove artifacts from the signals, extract features, and perform within-subject standardization. Ten features were extracted for each stimulus: SC area to full recovery, SC level, respiration line length, activity line length extracted from the gross body movement, pupil diameter amplitude, FP level, FP rise time from the first low point, standard deviation of interbeat interval (IBI) derived from the ECG signal, and IBI area to full recovery. Averages were computed for each emotion, and within-subject z-scores were computed for each feature for each subject.

3 Results

The specificity of each response feature to the emotion category of the evoking stimulus was analyzed using discriminant function analysis, where the feature values were independent variables and the emotion category was the grouping variable. The results of this analysis are shown as a confusion matrix in Table 1 for images and

Table 2 for sounds, where the chance level is 20%. It can be seen from these tables that classification accuracy was above chance for each emotion for both images and sounds. Note that this is post-hoc analysis – cross-validation of these findings against and independent set of data is needed to improve our level of confidence in response classification.

We then examined the physiological responses to internally generated emotions (via the mental imagery task). The discriminant function analysis results for these data are shown in Table 3. We find that the correspondence between the emotional state and response is similar to that found for external stimuli, except when the intended internal emotion was *fear*.

We next examined how the subjects' self-report of their emotional state correlated with the emotion the external stimulus was intended to evoke. Figure 1 summarizes the findings across stimulus modalities. We see that on average, the emotion experienced most strongly by subjects corresponded to the emotion the stimulus was supposed to evoke.

4 Discussion

In this study, we wished to quantify indirect correlates of emotional state, particularly in autonomic physiological responses. The approach was to use established corpora of acoustic and visual stimuli purported to evoke specific emotions, and to examine relationships between stimuli and responses.

The results shown in Table 1 indicate that a linear combination of the set of physiological response features is significantly correlated with the stimulus category. The differences between the values for images and sounds suggest that auditory and visual stimuli result in slightly different physiological responses.

Table 1. Classification percentages for image (I) and sound (S) stimuli

	Disgust		Sadness		Fear		Anger		Happiness	
	I	S	I	S	I	S	I	S	I	S
Disgust	**58.6**	**50.0**	13.8	10.0	3.4	20.0	13.8	20.0	10.3	0.0
Sadness	6.9	6.7	**48.3**	**56.7**	10.3	13.3	24.1	10.0	10.3	13.3
Fear	3.4	10.0	20.7	20.0	**55.2**	**43.3**	6.9	6.7	13.8	20.0
Anger	24.1	13.3	6.9	3.3	17.2	10.0	**44.8**	**66.7**	6.9	6.7
Happiness	17.2	6.7	6.9	23.3	10.3	10.0	3.4	13.3	**62.1**	**46.7**

Table 2 shows that different emotional states evoked internally by mental imagery can also produce significantly different physiological responses. However, the differences between Tables 1 and 2 suggest that either the internal emotional states or the physiological responses produced by mental imagery may be different from those produced by corresponding external stimuli.

Finally, Figure 1 suggests that the stimuli in the corpora can evoke emotional responses with reasonable accuracy (as assessed by the subject). However, the evoked state is a mixture of different emotions. This dependence between the emotional categories could be used in optimizing the design of a classifier that uses physiological responses.

Table 2. Classification percentages for internal Mental Imagery

	Disgust	Sadness	Fear	Anger	Happiness
Disgust	**53.3**	10.0	6.7	13.3	16.7
Sadness	10.0	**53.3**	6.7	6.7	23.3
Fear	20.0	16.7	**16.7**	20.0	26.7
Anger	16.7	10.0	20.0	**50.0**	3.3
Happiness	0.0	20.0	20.0	13.3	**46.7**

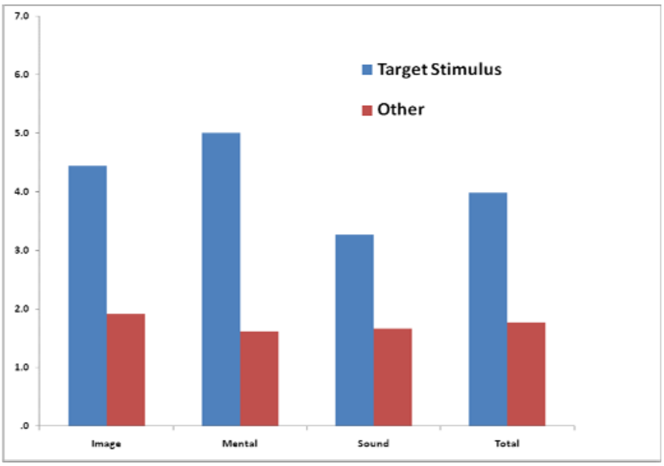

Fig. 1. Self-reported emotional responses to standard stimuli

Our measurements suggest that physiology offers a promising way to identify emotion, but the mappings from stimulus to emotional state and from emotion to physiology are subject to ambiguity. While our current results cannot resolve whether these ambiguities arise from systematic inter-subject differences or from large trial-to-trial variability within each subject, future studies will re-examine the data to develop subject-specific emotion inference methods, and study the test-retest reliability of these methods.

References

1. Bradley, M., Lang, P.J.: The International affective digitized sounds (IADS) stimuli, instruction manual and affective ratings: NIMH Center for the Study of Emotion and Attention (1999)
2. Brave, S., Nass, C.: Emotion in human-computer interaction. The human-computer interaction handbook: fundamentals, evolving technologies and emerging applications, 81–96 (2002)
3. Cowie, R., Douglas-Cowie, E., Tsapatsoulis, N., Votsis, G., Kollias, S., Fellenz, W., et al.: Emotion recognition in human-computer interaction. IEEE Signal Processing Magazine 18(1), 32–80 (2001)

4. Ekman, P., Levenson, R.W., Friesen, W.V.: Autonomic nervous system activity distinguishes among emotions. Science 221(4616), 1208 (1983)
5. Fasel, B., Luettin, J.: Automatic facial expression analysis: a survey. Pattern Recognition 36(1), 259–275 (2003)
6. Karg, M., Kuhnlenz, K., Buss, M.: Recognition of affect based on gait patterns. IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics 40(4), 1050–1061
7. Lang, P.J., Greenwald, M.K., Bradley, M.M., Hamm, A.O.: Looking at pictures: Affective, facial, visceral, and behavioral reactions. Psychophysiology 30(3), 261–273 (1993)
8. Levenson, R.W., Ekman, P., Friesen, W.V.: Voluntary facial action generates emotion-specific autonomic nervous system activity. Psychophysiology 27(4), 363–384 (1990)
9. Mitra, S., Acharya, T.: Gesture recognition: A survey. IEEE Transactions on, Systems, Man, and Cybernetics, Part C: Applications and Reviews 37(3), 311–324 (2007)
10. Murray, I.R., Arnott, J.L.: Toward the simulation of emotion in synthetic speech: A review of the literature on human vocal emotion. Journal of the Acoustical Society of America (1993)
11. Pantic, M., Rothkrantz, L.J.M.: Automatic analysis of facial expressions: The state of the art. IEEE Transactions on, Pattern Analysis and Machine Intelligence 22(12), 1424–1445 (2000)
12. Parkinson, B.: Emotions are social. Br. J. Psychol. 87(Pt 4), 663–683 (1996)