Applicability of Multi-modal Electrophysiological Data Acquisition and Processing to Emotion Recognition

Filipe Canento[1], Hugo Silva[1,2] and Ana Fred[1]

[1] Instituto de Telecomunicações, IST-UTL, Lisbon, Portugal
[2] PLUX – Wireless Biosignals, Lisbon, Portugal

Abstract. We present an overview and study on the applicability of multimodal electrophysiological data acquisition and processing to emotion recognition. We build on previous work in the field and further explore the emotion elicitation process, by using videos to stimulate emotions in several participants. Electrophysiological data from Electrocardiography (ECG), Blood Volume Pulse (BVP), Electrodermal Activity (EDA), Respiration (RESP), Electromyography (EMG), and Peripheral Temperature (SKT) sensors was acquired and used to classify the negative and positive emotions. We evaluate the emotional status identification accuracy both in terms of the target emotions and those reported by the participants, with recognition rates above 70% through Leave One Out Cross Validation (LOOCV) with a k-NN Classifier.

1 Introduction

Over the last years, different authors have studied emotions and their components and concluded about their crucial role in numerous areas of human life such as problem solving, social interaction, decision-making, perception, and motivation, [7]. Emotions are composed of two parts: a psychological and a physiological part. The former is related with the individual cognitive aspect of emotion; the latter has to do with the physiological responses that occur when an individual experiences an emotion. The use of biosignals to study emotions is a growing research field with more and more applications, [15].

In this paper we present an overview and study on the applicability of multimodal electrophysiological data acquisition and processing to emotion recognition. We developed a protocol for emotion elicitation and biosignal acquisition, for which preliminary results were presented in [2]. The rest of the paper is organized as follows: in Section 2 a review of the State-of-the-Art in emotion recognition is given; Section 3 summarizes the methodology and experimental setup proposed in; in Section 4, we evaluate the emotion elicitation procedure, and present the emotion classification results; Section 5 outlines the main conclusions and presents ideas for future work.

Canento F., Silva H. and Fred A..
Applicability of Multi-modal Electrophysiological Data Acquisition and Processing to Emotion Recognition.
DOI: 10.5220/0003891800590070
In *Proceedings of the 2nd International Workshop on Computing Paradigms for Mental Health* (MindCare-2012), pages 59-70
ISBN: 978-989-8425-92-8

Table 1. Summary of emotion recognition studies.

Year	Reference	Recognition rate
2001	[16]	81%
2004	[11]	64-97%
2004	[13]	61.8%
2006	[12]	71%
2009	[10]	86.3%
2010	[15]	61%
2011	[2]	30-97.5%

2 State-of-the-art

Emotion recognition using electrophysiological data is one of the branches of the Affective Computing field: a growing research field that merges emotions and computers in many different applications (see [18] and references therein). Table 1 summarizes some results found in State-of-the-Art work for emotion recognition using biosignals. The work by [16] sought the classification of 8 emotions from BVP, RESP, EDA, and EMG data; tests were performed in 1 subject with 81% recognition rates.

In 2004, Haag et al. [11] used Neural Networks (NN) and obtained a classification accuracy ranging from 64% to 97% for two components of emotion (arousal and valence) of 1 subject; the authors used EMG, ECG, RESP, EDA, SKT, and BVP data. By arousal we are referring to the physical arousal response to an emotional stimulus (e.g., a stimulus may provoke excitement and thus high arousal or it may be boring and provoke a low arousal response) and valence indicates whether an emotion is negative, neutral, or positive.

In [13], the authors used data from the ECG, EDA, and SKT to classify 4 emotions of 175 subjects using Support Vector Machines (SVMs); the accuracy was 61.8%. Leon *et al.* [12] also used NN in the pursuit of distinguishing positive, negative, and neutral emotions of 8 subjects; they used data from the BVP and EDA and had recognition rates of 71%.

In [10], data from EEG, BVP, and EDA was also used to classify 4 emotions of a subject while studying; they applied SVMs and k-Nearest Neighbors (k-NN) obtaining a best result of 86.3%. In 2010, [15] presented an emotion classification framework with Analysis of Variance (ANOVA), Principal Component Analysis (PCA), k-NN, SVM, and NN; an accuracy of 61% was achieved with the use of EMGs and EDA data to classify positive, negative, and neutral emotions of 21 subjects.

Recently, our team proposed a multimodal biosignal (ECG, BVP, EDA, RESP, EMGs, and SKT) sensor data handling for emotion recognition, [2]; we applied k-NN (k=5) to classify positive, negative, neutral, and a mix of different emotions of 20 subjects with recognition rates in the 30-97.5% range.

3 Methodology, Experimental Setup and Data Acquisition

Our team has been researching in Behavioral Biometrics and Affective Computing since 2007 when a project called HiMotion began, [5]. Within that project, a protocol was proposed to monitor Human Computer Interaction and acquire different electrophysiological signals for the study of behavioral biometrics, [3].

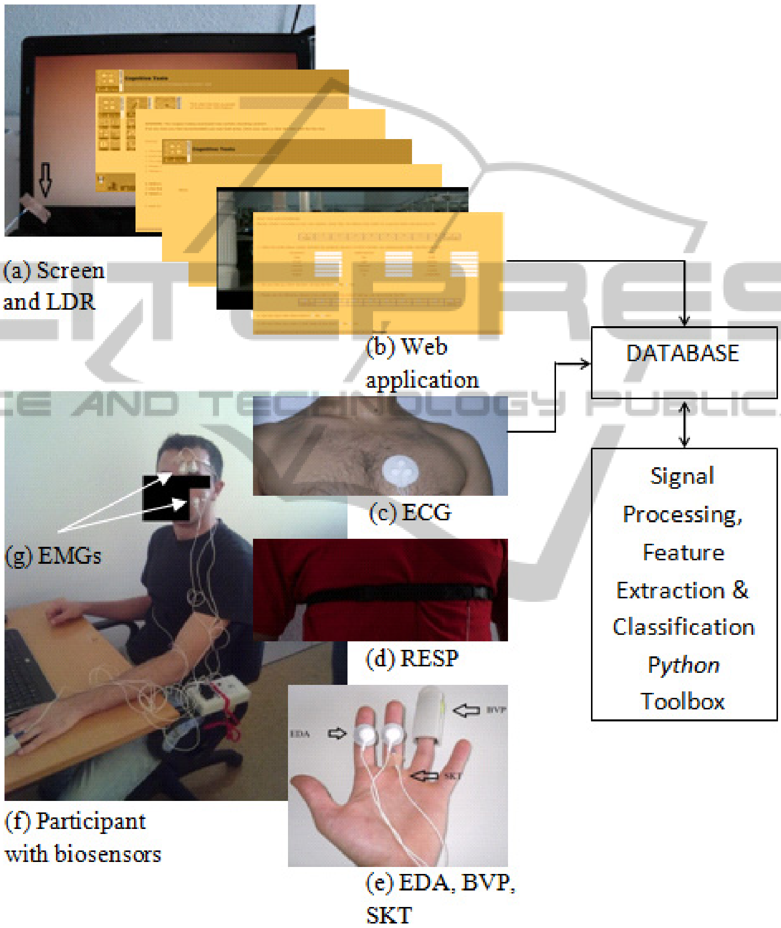


Fig. 1. Experimental setup and system architecture proposed in [2].

Later, in [1] and [2], we build upon the developed tools and results obtained and added an emotion elicitation component so that we could study how biosignals and emotions relate to each other. To elicit emotions, various techniques are available, [1]. We decided to use videos as emotional stimulus as they are easy to use and provide reasonable results, [17], [19]. Based on the experience setup by [17] and [19], we designed a Web application for video visualization.

The experience took the participant through the steps of Figure 3: (a) welcome page; (b) participant information; (c) protocol briefing; (d) light brown screen time for a period of 30 seconds; (e) full screen video; (f) questionnaire about the emotions felt during the video. Steps (d), (e) and (f) were repeated for a sequence of different videos. Step (c) has the objective of briefing the participant about the experience; step (d) is a 30 second period with no emotional stimulus so that the participant could relax and return to the baseline emotional state after each video; step (f) is a questionnaire used to retrieve the participants opinion about the emotions felt during the video.

The experimental setup and system architecture used is presented in Figure 1: we have a participant interacting with the Web application, with a set of seven biosensors attached to his/her hand, chest and face: Electrocardiography (ECG), Blood Volume Pulse (BVP), Electrodermal Activity (EDA), Respiration (RESP), Electromyography (EMG), and Peripheral Temperature (SKT) . The biosignals data is acquired using a bioPLUX research, wireless biosignal acquisition unit and corresponding set of sensors [6]; this information is then saved in a database along with information gathered by the Web application.

Synchrony between the biosignal and the Web application data is achieved through the use of a Light Dependent Resistor (LDR). This sensor outputs different values for different light values and so we placed it at the lower left corner of the screen where the color changes from light brown to black when a video is being played (an emotion is being elicited). We have also developed a Python toolbox to process the biosignals and apply feature extraction and classification techniques, [2].

4 Experimental Results

4.1 Emotion Elicitation

Table 2 summarizes the information retrieved by the video questionnaires, described earlier, for all the participants. As in [17], ***intensity*** refers to "*whether a film receives a high mean report on the target emotion relative to other candidate films*"; ***discreteness*** is the ratio between the number of participants that felt the target emotion (one point or more than all other emotions) and the total number of participants. We have also asked the users to rate the valence of their emotions in a 0-9 scale (0 stands for very negative emotion and 9 for very positive emotion).

Different conclusions can be drawn from the obtained data. First, we wanted to elicit 8 different emotional states (target emotions) and the participants reported 22 different emotions (see column 2 of Table 2 and Notes 1-4 of Table 4). As we can see, different people have different reactions for the same video as the reported emotions vary within the same film. Also, the target emotion is not achieved for all cases and all individuals. Overall, the Sadness, Disgust, and Amusement videos had the best results as the mean valence reported fell within the expected range (below 5 for the first three cases and above 5 in the last one) and had also higher intensity and discreteness levels. Fear is difficult to elicit, as people tend to reveal anxiety or interest about the situation being presented.

Table 2. Summary of video information and feedback given by the participants.

Target Emotion	Reported emotions (Most Common)	Reported valence	Intensity	Discreteness
Neutral 1 (60 sec)	Confusion/Boredom	2-4-9	0	0
Neutral 2 (80 sec)	Nothing/Pity/Love/Interest	2-4-9	0.28	0.33
Sadness 1 (90 sec)	Sadness/Uncomfortable	0-3-7	0.54	0.69
Sadness 2 (173 sec)	Sadness	0-2-6	0.77	0.89
Anger 1 (90 sec)	Anger/Disgust	1-3-6	0.39	0.62
Anger 2 (254 sec)	Anger/Anxiety	0-2-5	0.43	0.56
Surprise 1 (16sec)	Anxiety/Interest/Fear	1-4-8	0.09	0.15
Surprise 2 (47sec)	Confusion/Fear/Anxiety	1-3-9	0.11	0.22
Disgust 1 (60sec)	Disgust	0-2-6	0.83	0.92
Disgust 2 (65sec)	Disgust/Interest	0-2-5	0.27	0.33
Fear 1 (82sec)	Anxiety/Interest	2-4-6	0.10	0.15
Fear 2 (207sec)	Anxiety	0-3-7	0	0
Amusement 1 (155sec)	Amusement/Surprise	3-5-9	0.50	0.69
Amusement 2 (247sec)	Amusement	0-6-9	0.65	0.78
Happiness (87sec)	Happiness/Amusement	4-6-9	0.56	0.89

4.2 Classification

After the electrophysiological data acquisition, we used our Python toolbox to process the biosignals, extract a set of relevant features, and for classification. Table 3 presents the extracted features for each biosignal. For a list of commonly extracted features in the emotion recognition field refer to [15].

The classification process employed a k-NN (k=5) classifier [20], [21], and to assess how the results would generalize to an independent data set we used the LOOCV technique. The k-NN classifier evaluates the k points closest (k-Nearest Neighbors) to a given input data point, x_i, and outputs a class label, c_i. Each neighbor belongs to a class and c_i is determined as the most predominant class among them. The k-Nearest Neighbors were found using the Euclidean distance. The LOOCV technique divides data into a test set composed of one sample point and a training set composed of the remaining sample points.

The authors in [2], achieved a classification accuracy ranging from 30% to 97.5% for different scenarios – last line of Table 1. The labels used for classification were the target emotions. However, as we have seen before, the targeted emotions do not match the emotions reported by the participants in all cases. With that in mind, we applied the same techniques used before but having the classification labels equal the reported emotions. Table 4 shows the results obtained for both cases. As we can observe, the recognition rates are better for the target emotions: it may have to do with the division between positive and negative emotions that sets Amusement, Happiness, Joy, Love, Interest, and Peaceful in the positive emotions group and Anger, Disgust, Anxiety, Fear, Confusion, Embarrassment, Bored, Contempt, Shame, Powerless, Pity, Sadness, Touched, Scared, Surprise, and Unhappiness in the negative emotions group; for a future work, other criterions should be used such as the emotion valence reported by the participants.

Table 3. List of extracted features for each biosignal. μ: mean; σ: standard deviation; $σ^2$: variance; AD: absolute deviation; RMS: Root Mean Square; SCL: Skin Conductivity Level; SCRs: Skin Conductivity Responses; IBI: Inter Beat Interval; RMSSD: Root Mean Sum of Squared Differences.

Biosignal	**Features**
EMG	μ,σ, $σ^2$, AD, RMS Skewness Kurtosis
EDA	μ of SCL σ, $σ^2$, AD Skewness Kurtosis Number of SCRs μ and σ of the SCRs amplitudes μ and σ of the SCRs rise times μ and σ of the SCRs ½ recovery times
SKT	μ, σ, $σ^2$, AD Skewness Kurtosis
ECG	Heart Rate σ of IBI RMSSD of IBI Power Spectrum of IBI
RESP	μ, σ, $σ^2$, AD Zero crossings Skewness Kurtosis
BVP	Envelope Heart Rate σ of IBI RMSSD of IBI Power Spectrum of IBI

Table 4. Classification results.

Labels	Reported Emotions[1]		Target Emotions[2]	
	Positive (Amusement) vs. **Negative** (Anger, Disgust, Sadness)	**All Positive**[3] vs. **All Negative**[4]	**Positive** (Amusement) vs. **Negative** (Anger, Disgust, Sadness)	**Positive** (Amusement, Happiness) vs. **Negative** (Anger, Disgust, Fear, Sadness, Surprise)
Accuracy	71.2%	70.7%	82.5%	81.9%

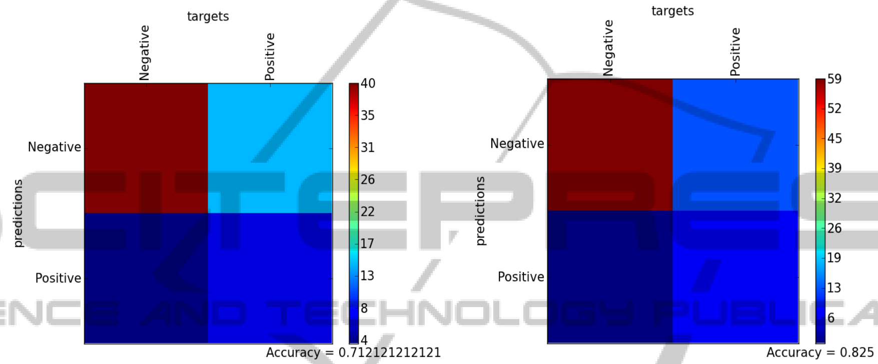


Fig. 2. Classification results for Positive vs. Negative emotions: reported emotions (left) and target emotions (right).

5 Discussion and Future Work

In this paper we approached the applicability of multi-modal electrophysiological data acquisition and processing to emotion recognition. We further explored and evaluated the emotion elicitation protocol proposed in [2]: it consists of a Web application for video viewing and the evaluation is based on the feedback given by the participants for each video used. On the one hand, videos for emotions such as the Sadness, Disgust, and Amusement scored the best results; on the other hand eliciting Fear turned out to be more difficult.

We wanted to elicit 8 emotions and the participants reported 22: different people have different reactions to the same emotional stimuli. New emotion classification results are presented based also on the information reported by the participants. Rec-

[1]The set of emotions that the individuals felt (Amusement, Happiness, Joy, Love, Interest, Peaceful, Anger, Disgust, Anxiety, Fear, Confusion, Embarrassment, Bored, Contempt, Shame, Powerless, Pity, Sadness, Touched, Scared, Surprise, Unhappiness)

[2]The set of emotions that we wanted to elicit (Neutral, Amusement/Happiness, Anger, Disgust, Sadness, Fear, Surprise)

[3]The set of positive emotions (Amusement, Happiness, Joy, Love, Interest, Peaceful)

[4]The set of negative emotions (Anger, Disgust, Anxiety, Fear, Confusion, Embarrassment, Bored, Contempt, Shame, Powerless, Pity, Sadness, Touched, Scared, Surprise, Unhappiness)

ognition rates above 70% are achieved when classifying positive and negative emotions using LOOCV estimates with a k-NN Classifier. For future work, classification based on criterions such as the emotion valence and arousal will be used; other emotion elicitation techniques such as pictures, sounds, games can also be inserted and tested in the developed Web application; acquiring new electrophysiological data and extend our current database is also a future goal.

Acknowledgements

This work was partially supported by the National Strategic Reference Framework (NSRF-QREN) programme under contract no. 3475 (Affective Mouse), and partially developed under the grant SFRH/BD/65248/2009 from Fundação para a Ciência e Tecnologia (FCT), whose support the authors gratefully acknowledge.

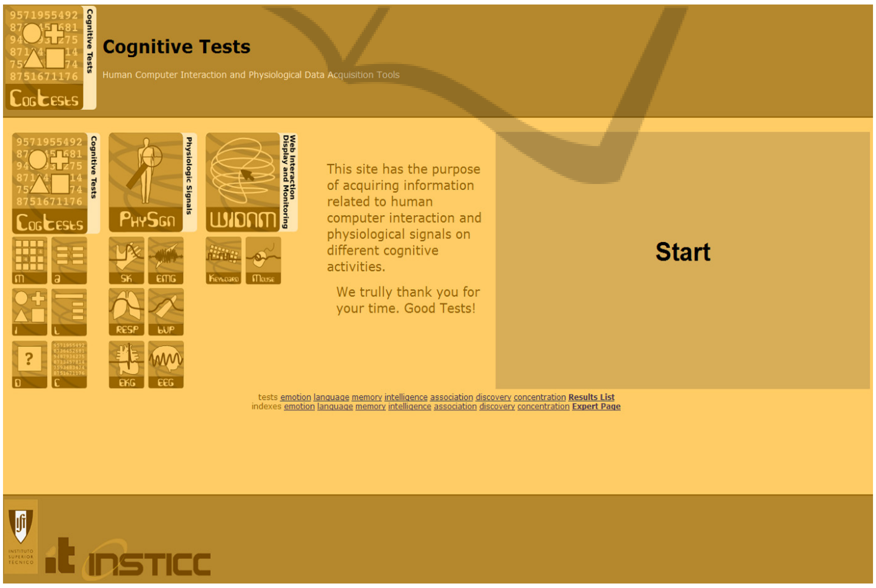
References

1. Filipe Canento. Affective mouse. Master's thesis, IST-UTL, 2011.
2. Filipe Canento, Ana Fred, Hugo Silva, Hugo Gamboa, and André Lourenço. Multimodal biosignal sensor data handling for emotion recognition. In Proceedings of the IEEE Sensors Conference, 2011.
3. Hugo Gamboa. Multi-Modal Behavioural Biometrics Based on HCI and Electrophysiology. PhD thesis, IST-UTL, 2006.
4. André Lourenço, Hugo Silva, and Ana Fred. Unveiling the biometric potential of Finger-Based ECG signals. Computational Intelligence and Neuroscience, 2011.
5. A. Fred, H. Gamboa, and H. Silva, "Himotion project," tech. rep., Universidade Técnica de Lisboa, Instituto Superior Técnico, 2007.
6. PLUX, "PLUX Website", www.plux.info, March 2011.
7. R. Picard, Affective Computing. MIT press, 1997.
8. J. Larsen, G. Berntson, K. Poehlmann, T. Ito, and J. Cacioppo, "The psychophysiology of emotion," in The handbook of emotions, pp. 180–195, Guilford, 2008.
9. M. Whang and J. Lim, "A physiological approach to affective computing," in Affective computing: Focus on Emotion Expression, Synthesis and Recognition (J. Or, ed.), pp. 309–318, In-Tech Education and Publishing, 2008.
10. L Shen, M.Wang, and R. Shen, "Affective e-learning: Using "emotional" data to improve learning in pervasive learning environment," Educational Technology & Society, 2009.
11. Haag, S. Goronzy, P. Schaich, and J. Williams, "Emotion recognition using bio-sensors: First steps towards an automatic system," in Affective Dialogue Systems: Lecture Notes in Computer Science, pp. 36–48, Ed. Springer Berlin, 2004.
12. E. Leon, G. Clarke, V. Callaghan, and F. Sepulveda, "A user-independent real-time emotion recognition system for software agents in domestic environments," Engineering Applications of Artificial Intelligence, 2006.
13. K. Kim, S. Bang, and S. Kim, "Emotion recognition system using short-term monitoring of physiological signals," Medical & Biological Engineering & Computing, 2004.
14. F. Hönig, A. Batliner, and E. Nöth, "Real-time recognition of the affective user state with physiological signals," in Proceedings of the Doctoral Consortium of the 2nd International Conference on Affective Computing and Intelligent Interaction, pp. 1–8, 2006.

15. E. van den Broek, V. Lisý, J. Janssen, J. Westerink, M. Schut, and K. Tuinenbreijer, “Affective man-machine interface: Unveiling human emotions through biosignals,” in Biomedical Engineering Systems and Technologies: BIOSTEC2009 Selected Revised papers (A. Fred, J. Filipe, and H. Gamboa, eds.), pp. 21–47, Springer-Verlag, 2010.
16. R. Picard, E. Vyzas, and J. Healey, “Toward machine emotional intelligence: Analysis of affective physiological state,” IEEE Transactions Pattern Analysis and Machine Intelligence, 2001.
17. J. Rottenberg, R. Ray, and J. Gross, “Emotion elicitation using films,” in The handbook of emotion elicitation and assessment (J. Coan and J. Allen, eds.), pp. 9–28, Oxford University Press Series in Affective Science, 2007.
18. R. Picard, Affective Computing Research Group at MIT, “Affective computing projects.” http://affect.media.mit.edu/projects.php, March 2011.
19. J. Hewig, D. Hagemann, J. Seifert, M. Gollwitzer, E. Naumann, and D. Bartussek, “Brief report: A revised film set for the induction of basic emotions,” Cognition & Emotion, 2005.
20. R. Duda, P. Hart, and D. Stork, Pattern Classification. Wiley, 2001.
21. C. Bishop, Pattern Recognition and Machine Learning. Springer, 2006

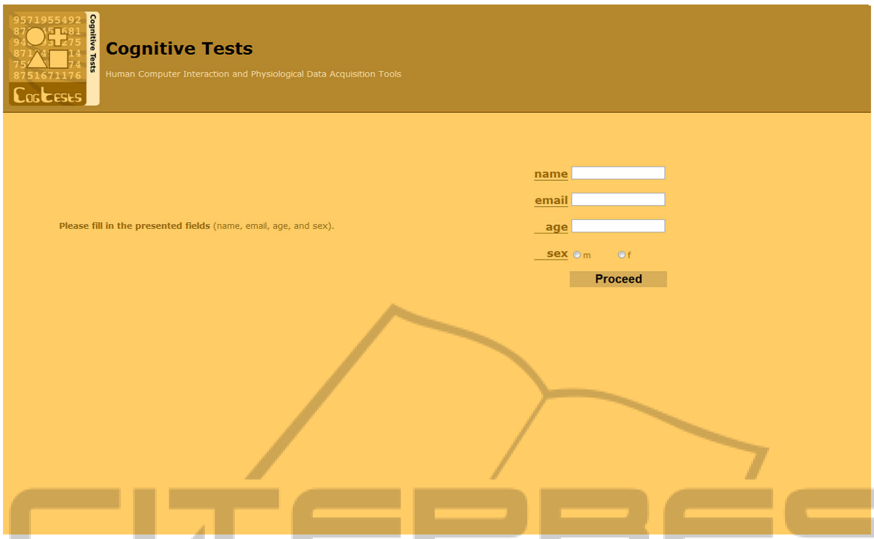
Appendix

Web application interface for emotion elicitation.

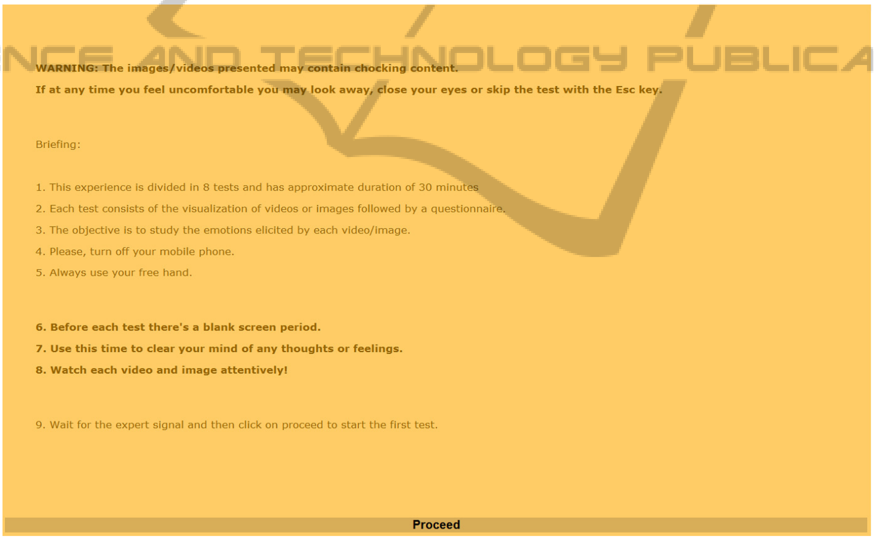


(a) Start page

Fig. 3. Web application for emotion elicitation using videos.



(b) Participant information page



(c) Protocol briefing page

Fig. 3. Web application for emotion elicitation using videos.(cont.)

(d) Blank page

(e) Video page

Fig. 3. Web application for emotion elicitation using videos. (cont.)

(f) Questionnaire page

Fig. 3. Web application for emotion elicitation using videos. (cont.)