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A Computational View of the Emotional Regulation of Disgust using Multimodal Sensors

Vidhathri Kota, Geeta Madhav Gali and Ifeoma Nwogu
Department of Computer Science, Rochester Institute of Technology, Rochester, USA

***Abstract*— Emotion regulation can be characterized by different activities that attempt to alter an emotional response, whether behavioral, physiological or neurological. The two most widely adopted strategies, cognitive reappraisal and expressive suppression are explored in this study, specifically in the context of disgust. Study participants (N = 21) experienced disgust via video exposure, and were instructed to either regulate their emotions or express them freely. If regulating, they were required to either cognitively reappraise or suppress their emotional experiences while viewing the videos. Video recordings of the participants' faces were taken during the experiment and electrocardiogram (ECG), electromyography (EMG), and galvanic skin response (GSR) readings were also collected for further analysis. We compared the participants behavioral (facial musculature movements) and physiological (GSR and heart rate) responses as they aimed to alter their emotional responses and computationally determined that when responding to disgust stimuli, the signals recorded during suppression and free expression were very similar, whereas those recorded during cognitive reappraisal were significantly different,. Thus, in the context of this study, from a signal analysis perspective, we conclude that emotion regulation via cognitive reappraisal significantly alters participants' physiological responses to disgust, unlike regulation via suppression.**

I. Introduction

Emotion regulation can be defined as the processes by which individuals influence their experiences and expressions of emotions [1]. Richards and Gross [2] presented two forms of emotion regulation strategies, (i) suppression where the individual aims to stifle any response or expressions of to the felt emotion; and (ii) reappraisal where the individual attempts to have a cognitive change in the assessment of the emotion-inducing stimulus.

Although several studies have been undertaken to examine these two distinct regulation strategies, their effectiveness in the context of different emotions still remains unclear. For example, Olantunji et. al [3] showed that the physiological manifestations of fear and disgust were of similar intensity on average when participants attempted to suppress their emotions, but when reappraising, the intensity of fear remained high while that of disgust decreased, suggesting that it might be easier to reappraise the disgust emotion than fear. Disgust as a negative emotion is said to reliably induce robust emotional experiences and emotion-expressive behaviors [4], and unlike other emotions such as fear or anger, is not as context dependent. What might make one person angry or sad may not necessarily have the same effect on another. For this reason, in this work, we focus specifically on studying emotion regulation in the context of disgust.

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In our work, we refer to three states of emotional regulation (i) cognitive reappraisal; (ii) suppressed emotion; and (iii) free expression (or no regulation). Although in the strict sense, the third state is not a form of emotional regulation, for computational purposes, we treat it as such to allow us compare the results readily across the different paradigms.

We are therefore interested in a computational evaluation and visualization of how cognitive reappraisal and emotion suppression are manifested behaviorally and physiologically across different modalities.

A. Measurements

To address, we conducted a multimodal study of emotion regulation to observe participants' behaviors when responding to disgust-eliciting stimuli. The modalities we used for obtaining measurements included: electromyography (EMG), electrocardiogram (ECG) from which we deduced heart rate, galvanic skin response (GSR) [7]; and facial movements via a video camera.

II. Data Collection

Data for the study was collected from 21 participants recruited across the college campus, between the ages 21 and 30 years of age; nine female and thirteen male. The project participants initially provided verbal consent and were then fitted with the different sensors - EEG[1], EMG, ECG and GSR. A video recorder was also set to capture image data from their faces while they watched emotion inducing videos from a computer desktop in the lab. The participants were briefed on the nature of the experiment and instructed on what it meant to freely express, suppress and cognitively reappraise an emotion. To reduce the cognitive load during reappraisal, the participants were instructed to initially call into mind, a very amusing situation in which they found themselves in the past. They were to use this memory to reappraise the disgust emotion during that stage of the experiment.

Each participant watched a video containing 6 different emotion-eliciting stimuli. Three of these would evoke the emotion disgust, while the other three would evoke a happy emotion based on amusement (We do not report on amusement in this paper). Between each pair of stimuli, a neutral calming video was shown to the participant, to reduce the

[1]EEG analysis was not considered in this report.

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effects of any previous stimuli and reset any past activations back to baseline.

For each stimulus, the participants was required to either freely express, suppress or reappraise while watching the video segment. The entire video contained cue-cards cuing the participant on when and how to regulate or express their emotion for the upcoming stimulus.

The EMG, ECG and GSR readings were all measured from different channels of the same BiopacMP 150 system and sampled at 1000 Hz with the Biopac Acqknowledge software. A webcam was also connected to one of the BiopacMP channels. A participant initiated the experiment by clicking a start button which fired off a trigger to begin collecting data from all the sensors at the BiopacMP channels. This allowed us to do-away with any laborious synchronization methods to align the signals after collection.

III. Processing the data collected

A. GSR data

GSR data was down-sampled and smoothed with a median filter whose specifications were as recommended by the equipment manufacturers. To account for highly sensitive people whose baseline GSR readings could be high compared to others, thus biasing the readings to appear more intense that necessary, we (0,1) normalized each participant's video. Also, to account for residual effects of applying different stimuli in the same experiment, a small window was selected at the end of the baseline (neutral stimulus), just before the stimulus was set to begin. The average GSR value was computed in that window, and then subtracted from each value in the ensuing stimulus readings. The resulting value (after subtraction) is referred to as the *mean-adjusted change score*.

GSR feature extraction: Every GSR signal has latency, the gap between the presentation of the stimuli and the onset of the response. This usually comes 1-5 seconds after the stimuli has been presented. The onset is the voltage at which the GSR rapidly rises to reach its peak amplitude. For peak detection, we find the peak onsets and their subsequent offsets, and calculate the number of peaks in a two second window.

The GSR features extracted therefore include *maximum peak amplitude*, *minimum peak amplitude*, *standard deviation*, *mean of GSR amplitudes*, *number of peaks per interval* and *signal entropy* given as $h = -\sum_i^n p_i \log(p_i)$;
where the GSR signal containing n points is binned into a normalized histogram and p_i is the probability of occurrence of each point i in the signal.

B. Facial skeletal muscles

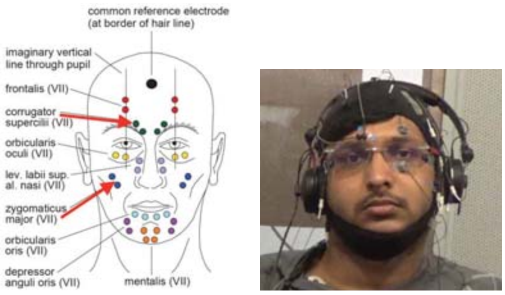
For capturing behavioral expressions of emotion via facial skeletal muscle movements, we used two approaches: (1) Recording the particiapants' faces while performing the experiment and then localizing action units (AUs) on their faces. (2) We also recorded two channels of EMG readings from the face.

1) Facial expressions from face videos: Although OpenFace is a popularly used facial analysis toolkit, which has been shown to do a good job capturing specific action units such as AU6 and AU12 [8], unfortunately, in this study, we were unable to use the tool as it was incapable of capturing the main action unit (AU9) involved in expressing disgust, even when the participants freely expressed the emotion[2] .

We therefore utilized the iMotions® emotion FACS (EM-FACS) tool to detect the facial expressions for the participants.

2) Facial expressions from EMG measures: Facial EMG is generally recorded bipolarly with small surface electrodes located in close proximity to each other [9]. Using EMG, even the weakest responses can be detected, especially since most facial muscles involved in facial expressions are located close to the surface of the skin.

Figure 1 left shows an exhaustive set of the locations on the face where electrodes can be placed to measure facial EMG activities. For this work, due to limited resources, we could only use 2 EMG electrodes, the corrugator supercilii and the zygomaticus major shown with red arrows in the left image. We evaluated the movements in the corrugator supercilii as it has been shown that fear and disgust cause activity in this muscle [10].



(a) (b)

Fig. 1. Left image shows an exhaustive set of locations where EMG measures can be taken on the face. The red arrows show the two locations we employed for this study. (image used by permission of author [9]). The right image shows the face of a participant fitted with the EMG and other sensors.

The raw EMG data is first high-pass filtered to remove the influence of artifacts such as eye movements, eye blinks, motion due to breathing, swallowing, etc. The resulting signal amplitude was then estimated by calculating the mean rectified EMG measures and then low-pass filtered.

C. ECG data

The electrocardiogram (ECG) measures the electrical activity of the heart, and on the assumption that none of our participants suffered from irregular heart rhythms, we successfully calculated the average heart rate from the ECG measures by filtering and analyzing the QRS waves. Heart rate values were computed every 100ms for each participant.

[2]This could also be in line with the findings by Jinhyun Cheong that OpenFace does not effectively capture all the AUs it aims to (`http://jinhyuncheong.com/jekyll/update/2017/10/20/Face-analysis-software-comparison.html`)

D. Self-report

During the experiment, after each stimulus was completed, the video was paused and participants were required to self report their valence levels (on a scale of 1-7) as well as the intensity of emotion they felt (also on a scale of 1-7) during the last stimulus presented.

IV. Analysis and Results

In this section, we first present the results of our computation to determine if there are differences in the the GSR time-series sequences recorded during the three states of emotion regulation of disgust.
Note:All graphs presented are divided into three sections, where the first section represents the pre-stimulus baseline (participant watching a calming video), the next section represents the period where the participant is viewing the emotion-inducing video and the last section the post-stimulus period, where the participant again views a calming video.

A. Results from GSR analysis

For the GSR data, a 900-frame sliding window with an offset of 50 was used to extract multiple segments from the original participant video. This resulted in about 400 samples per video. Depending on where in video the sample fell, it was labeled as one of three classes - freely expressed, reappraised or suppressed. The different GSR properties described in Section III were obtained for each of the segments.

The GSR data was prepared for 3-class classification using both a linear support vector machine (SVM) and a gated recursive neural network (GRU) for classification. The data was split by participant into $\approx$ $80\% - 20\%$ for 5-fold cross validation. A participant's data could only be used for training or testing, but not both. Table I shows the confusion matrices resulting from the two classifiers.

TABLE I

Confusion matrices from classifying the types of emotion regulation of disgust from GSR data

Results from the SVM classifier			
	Express	Suppress	Reappraise
Express	0.19	0.38	0.42
Suppress	0.24	0.40	0.34
Reappraise	0.18	0.18	0.62
Results from the GRU classifier			
	Express	Suppress	Reappraise
Express	0.19	0.31	0.49
Suppress	0.26	0.38	0.35
Reappraise	0.20	0.12	0.68

The most dominant repeat support vector responsible for the classification was *max value*, thus indicating that the signal intensity was most responsible for the classification. Interestingly, for both classifiers, the freely expressed and suppressed regulations of disgust were significantly confused with each, but distinctly different from reappraisal.

The parameters of the GRU are: learning rate = 1e-4; loss function = cross entropy Loss; optimizer = Adam; input sequence length = 100; # GRU layers = 3; # linear layers = 2; batch size = 48

Figures 2 show the GSR measures obtained for the three states of emotion regulation of disgust. We present this to demonstrate that cognitive reappraisal tends to be distinctly different at the physiological level, based on GSR readings.

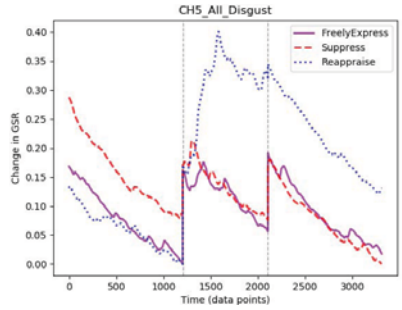


Fig. 2. Mean-adjusted GSR readings for the three different regulation types for disgust across all participants

B. Results from analyzing facial skeletal muscles

1) Results from iMotions : Figure 3 shows the results obtained from the iMotions emotion analyzing software. The figure shows the normalized and aggregated values across all participants. The patterns of the three emotion regulations strategies suggest that the participants behaviorally regulated their emotions, although the AUs measured by iMotions indicate that there was some leakage in the face as the stimulus went on .

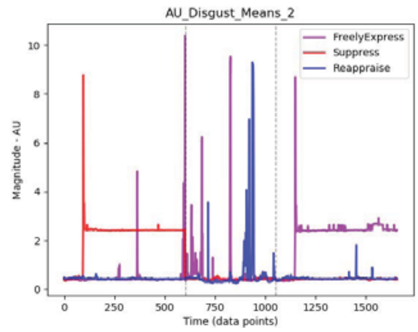


Fig. 3. Normalized aggregated readings across all participants, for the 3 regulation types when viewing disgust-eliciting videos.

2) Results from EMG - corrugator supercilii electrode: Unfortunately, we were unable to obtain reliable signals from the electrode located at the zygomaticus major, which would have been very similar to AU9, the nose wrinkler primarily responsible for measuring disgust on the face. Nevertheless, because AU4 is also quite prominent for disgust, the corrugator muscles gets activated when expressing this emotion. Firthermore, Rymarczyk *et al.* showed that disgust causes activity in the corrugator supercilii muscle.

Figure 4 shows the combined EMG measures obtained for all the participants, for the three states of emotion regulation from the placing the corrugator supercilii electrode on the faces of the participants.

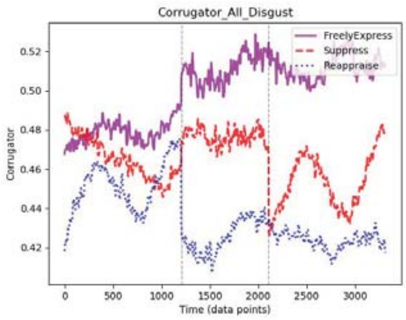


Fig. 4. The mean-adjusted EMG readings from the electrode at the corrugator muscle, for the three emotion regulation type for disgust across all participants

The EMG signal is most prominent when the participants freely express their disgust emotions, is significantly lower when the participants attempt to suppress their disgust, and is least active during the reappraisal phase. Empirically the evidence demonstrates that at the behavioral level, cognitive reappraisal tends to be distinctly different from the other forms of regulation.

C. Results from analyzing heart rate data

After translating the ECG signals to heart rate (beats-per-minute), the data for the participants were aggregated over same time intervals and plotted. Figure 5 shows the combined heart rate data obtained for all the participants, for the three regulation types for disgust. Again, cognitive reappraisal still creates a distinct physiological response from either freely expressing or suppressing emotion (positive or negative).

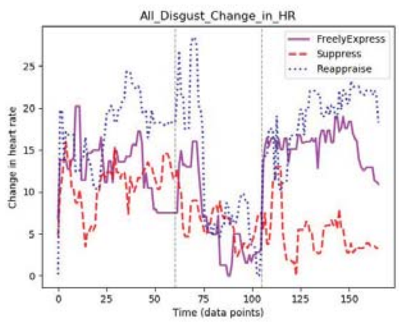


Fig. 5. The mean-adjusted heart rate for the three regulation types for disgust

From Figure 5, cognitive reappraisal manifests differently from the other two forms of emotion regulation. As predicted in the literature [11], disgust-related stimuli are generally associated with lowered heart rate during the viewing session; thus indicating in our experiment that cognitive reappraisal reduced the effect of the disgust stimulus (by increasing the heart rate), unlike emotion suppression.

D. Self-reporting results

We aggregated the self-report results made by each of the participants after each stimulus was presented and Table II provides summary statistics across all 21 study participants.

TABLE II
SUMMARY STATISTICS FROM SELF-REPORTED MEASURES

	Disgust Valence	*Disgust Intensity*
Reappraisal Mean	3.29	4.67
Reappraisal Std_dev	1.42	1.83
Suppression Mean	3.19	4.57
Suppression Std_dev	1.59	1.68
Freely express Mean	2.67	4.95
Freely express Std_dev	1.36	1.36

Results from self-reporting did not indicate as strong a difference as observed with other physiological and behavioral measures. Unfortunately, from offline discussions, some participants were confused by the expectations of the self-reporting tool. Trying to quantify one's level of valence as well as the intensity of emotion felt, in the middle of the study might not have been the most effective way to obtain this data.

V. DISCUSSION AND CONCLUSION

We have shown by analyzing facial expressions and muscular movements, that the participants successfully regulated the disgust emotion **behaviorally**, as instructed. **Physiologically**, based on GSR analysis, participants overall tended to have a significant increase in arousal when reappraising disgust, which is quite consistent with the literature (disgust generally lowers arousal levels). This was not the case when suppressing or freely expressing the emotion. This point was further illustrated by the results of two classifiers, where the two regulation types were confused, whereas the reappraised regulation type was distinct.

As expected, overall heart rate went down when the participants were exposed to disgust emotions. Heart rate data provided similar insights as the previous physiological measures, but was not as distinct in delineating between the three forms of regulation. These observations are loosely supported from the literature which suggest that the cardiovascular system is not necessarily a reliable measure for behavioral or physiological expressions of negative emotions such as fear and disgust [3]. Lastly, unfortunately, based on offline reports from several participants, the self-reports from this study were not reliable.

In summary, we have clearly shown from our study, that the physiological manifestations of disgust strongly support the claims that cognitive reappraisal presents significantly differently from emotion suppression or freely expressed emotion. We demonstrated this most successfully with our analysis of GSR data. Even with this limited data, we plan to make our multimodal measures publicly available for other researchers who are interested in computationally analyzing emotion regulation methods.

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