Regulation of contagion along a queue of emotional agents

Joseph Kempel¹, David Bridget², Sachit Butail³

Abstract—The communication of fear information within large human crowds often results in escape waves characterized by the contagion of heightened emotional arousal and then ensuing flight response between individuals. Once onset occurs, such escape waves spread fast and are difficult to control, leading to crowd disasters. In this context, a yet unexplored control parameter may exist at the level of an individual, specifically in their ability to put their emotions in check. The process of controlling one’s emotion is called emotion regulation, and in this paper, we investigate the effect of emotion regulation on the spread of contagion. In a data-driven approach, we use experimental electroencephalogram (EEG) data from a previously published study, where individuals were exposed to images that aroused negative emotions such as fear, to first estimate a dynamical model of emotion generation. We then close the loop using proportional control to match data from the same study to represent the regulation of emotion by distraction. Next, we simulate a line of emotional agents, each represented by a closed loop control system, to investigate the effect of emotion regulation on the spread of contagion. This simple setup shows that emotion regulation can weaken the contagion in terms of the combined state of the group and the time it takes for a significant fraction of the group to reach a state of heightened fear. The framework described here presents a first step in a control-theoretic interpretation and modeling of emotion regulation and motivates future work in data-driven analysis of emotional contagion.

I. INTRODUCTION

The collective response of a group to a localized sudden stimulus often resembles a cascade of impulsive actions known as the ripple effect or escape wave [1]. While in animals, this reaction serves as an efficient predator avoidance strategy [2], in humans, the collective response to fear [3] can have fatal consequences [4]. At the heart of this phenomenon is the transmission of an emotion—fear in this case—expressed through body movements, and communicated through a large group of people over a span of a few seconds.

Emotional contagion consists of two components: the generation of emotion within an individual, and the communication of that emotion to another individual. The process of emotion generation has been modeled in [5], [6], [7]. In [5] an appraisal model of emotion is developed that generates emotion based on cognitive processes and past beliefs. The model is inspired from theoretical frameworks in psychology and aims to create a human-like autonomous agent. The authors in [6] develop a model that consists of multi-layered architecture consisting of cognition, emotion generation, and coping to impart realistic emotions to virtual characters. The model is tested in a user study where virtual characters were able to evoke empathetic reactions among real humans. The model proposed in [7] is based on Gross’s emotion regulation theory [8] and incorporates feedback loops that aim to attain a desired emotion response level by intercepting emotion generation through the four emotion regulation strategies. This model has many parameters that determine the level of emotion regulation by comparing the actual emotion level with a desired emotion response.

Inducing fear in large groups through communication of emotion has obvious safety concerns, and therefore a majority of work in this area has relied on building accurate models of contagion that qualitatively match the phenomena in terms of the user ability to recognize emotions [9], [10], and matching to real data [11]. Specifically, an agent-based model in [9], implements contagion in a consensus-like approach, with an agent absorbing the emotions of their neighbors. In [10], a proximity-based model of contagion is simulated with psychologically different crowds. The primary goal of these models is to simulate believable graphical animations of contagion. A mean-field approximation of the model described in [9] has been developed in [12] to study the effects of interaction weights and the consensus gain on the spread of contagion.

In this paper, we follow a data-driven approach in building a model of emotion generation. We interpret emotion generation and regulation in a control theoretic framework, where emotion is checked by an individual on the basis of their response to a certain situation. In this sense, our model is most similar to the one in [7]. Differently from [7], the approach used here results in a black-box model with fewer parameters. At the same time, the model is amenable to data fitting using emotion measurement data available from the literature.

In particular, we use methods from system identification and control theory to build a black-box model of an emotional agent, which is then used to investigate the effect of emotion regulation on simulated contagion. The model (plant) is estimated using electroencephalogram (EEG) data obtained from an experimental study in the literature [13]. Emotion regulation, or the ability to control one’s emotion, is then modeled in the form of a proportional control on the plant, fitted on EEG data from a relevant experimental condition in the same study [13]. Finally, to simulate contagion, emotional agents are simulated in a queue as they
interact with a realistic delay. We then investigate the effect of proportional control gain on the spread of contagion. The paper is organized as follows: we briefly give a background on emotion generation and emotion regulation in Section II; Section III presents the system identification of the emotion generation process based on EEG data obtained from [13]. In Section IV we investigate the effect of emotion regulation, modeled in the form of proportional control, on the spread of contagion along a line of emotional agents. Finally, these results are discussed in Section V.

II. EMOTION GENERATION AND REGULATION

A. Emotion Generation and Regulation

The expression of emotion consists of four distinct stages modeled in a sequential emotion generation process [8], [14]. These begin with the individual being in a situation, paying attention to it, interpreting the situation, and then responding to it [8]. The response to an emotion can serve to influence the control of emotion in a feedback loop, thereby modifying the response itself [8]. This is known as the emotion regulation process. Depending on the stage of emotion generation that is interrupted, emotion regulation can be applied early or later during emotion generation [8]. For example, the action of flight to a fear stimulus may be contained by deploying ones attention in another direction through distraction, or by cognitively reappraising the situation by attaching a trivial meaning to the stimulus itself.

Emotion regulation can be intrinsic or extrinsic [8]. Intrinsic emotion regulation takes place when an individual consciously or unconsciously regulates their own emotions. In contrast, extrinsic emotional regulation refers to reliance on external cues to aid in the regulation of emotion. The two widely used strategies for intrinsic emotion regulation are distraction and reappraisal [15], [16]. Distraction, which takes place during the attention deployment stage of emotion generation, involves consciously redirecting one’s attention away from the emotion-eliciting event and may aid in anxiety reduction [17]. Reappraisal, on the other hand, is implemented at a later stage of emotion generation, and involves attaching an alternate interpretation to the emotion-eliciting event [13].

B. Temporal Dynamics of Emotion Generation

In this paper, we use EEG data from a psychological experiment conducted to explore the temporal dynamics of emotion regulation in the laboratory [13]. Specifically, in [13], time-series from the average of multiple EEG signals were used to investigate the dynamics of two forms of emotion regulation: distraction and reappraisal [13]. In particular, a component of EEG called the late positive potential (LPP) was used. LPP is a positive rising signal of slow progression that is maximal at the central parietal sites of the brain [18]. Several studies have reported that the LPP is a more robust measurement for emotional arousal than the EEG signal itself [18], [19].

During the experiment in performed in [13], a white cross was presented to each participant for 2 seconds, followed by an instructional text image that consisted of the type of regulation to be deployed for 2 more seconds. A stimulus image that would induce negative emotions such as fear is then presented soon after for 5 seconds. All this while the EEG data of participants was recorded with a standard 42-node electrode headset [13].

III. SYSTEM IDENTIFICATION OF EMOTION GENERATION AND REGULATION DURING FEAR

In control theory, the evolution of the state of a linear dynamical system is represented by a differential equation that describes the response of a system to an arbitrary input [20]. Specifically, if the input is represented by time-series $u(t)$, and the output response is represented by $y(t)$, then the dynamics of a system can be represented by an $n^{th}$ order differential equation [20]

$$y^{(n)}(t) + a_1y^{(n-1)}(t) + \ldots + a_{(n-1)}y'(t) + a_ny(t) = b_0u^{(n)}(t) + b_1u^{(n-1)}(t) + \ldots + b_nu(t),$$

where $y^{(n)}(t)$ is the $n^{th}$ order derivative of $y(t)$, and $a_i, b_i$ are constant coefficients. Taking the Laplace transform of this equation converts $u(t)$ and $y(t)$ into functions of complex variables, as $U(s)$ and $Y(s)$. The ratio $G_o(s) = Y(s)/U(s)$ describes the system response to an impulse input and is called a transfer function.

Given the response of a system to a known input, the transfer function can be estimated by a data-fitting process called system identification. This entails using input-output measurement data to construct a mathematical representation of a dynamical system. Control of the response of the dynamical system can be accomplished by closing the loop (Fig. 1) by feeding back $y(t)$ through a controller $G_c(s)$ and comparing the result with the input $u(t)$. Alternatively, the controller can also be designed to act on the difference $y(t) - u(t)$. The reason we apply the controller on the response instead of the difference is that by setting the controller to a zero value we automatically obtain the open loop system. The resulting transfer function of the closed-loop system is

$$G_{cl}(s) = \frac{G_o(s)}{1 + G_c(s)G_o(s)}$$

![Fig. 1. Schematic representation of a system with feedback connection.](image)

In our case, we assume that the emotional state of an individual is measured by the LPP data [13]. We further assume that the presentation of a stimulus is in the form of a visual action or image can generate emotion. In the context of behavioral contagion, we used this setup to represent the
fear response to physical cues from the individuals who react prior. Accordingly, here, we use $y(t)$ to denote the emotional response and $u(t)$ to denote the emotional state generated by the input both measured in terms of LPP. Therefore, the open loop setup implies the situation where a user lets their emotion go unchecked, even if they are aware of a desired emotional state, and the closed loop implies the process of regulating ones emotion by putting them in check so that it matches a desired emotional state.

A. Data-Driven Transfer Function of Emotion Generation

System identification requires data in the form of an input and output time series. In [13], average LPP data is presented for four experimental conditions, of which we highlight the two that we use: negative-watch which consists of response of an individual to a stimulus image for 5 seconds without emotion regulation, and negative-distract which consists of using distraction to regulate the emotional response to the stimulus image (Fig. 1). We represent the presentation of the stimulus image as a step input of a certain magnitude, and use the negative watch data to represent an open loop system. Consequently, the negative-distract condition data is used to represent a closed-loop system.

We estimate the transfer function representing the open-loop system using the MATLAB system identification toolbox. Specifically, the toolbox is used to identify the transfer function that best represents the LPP response data of negative-watch experimental condition. The response data was extracted from the corresponding figures by manually selecting points on the plot at an average resolution of 1 point per 3 milliseconds (Fig. 2). The data was then interpolated to obtain equally spaced points in time. A step function with a value of $3\mu V$ with a standard deviation of $\pm 0.49\mu V$ corresponding to the mean settling value of the response was used as the input. To locate the best data fit, we varied the order of the input within the candidate transfer function by varying the number of poles from 2 to 6, and zeros from 1 to one less than the number of poles. The improvement in overall data fit in terms of the residual error increased with the number of poles until fourth order at approximately 6%, after which the maximum improvement in data fit was less than 3%. The model output projected on top of actual response is shown in Figure 3. The corresponding fourth order transfer function that is used to model the emotion generation process is

$$G_o(s) = \left(\frac{1.1536 e^{-0.7} s - 1.5050 e^{-12}}{(s^4 + 0.005319 s^3 + 2.5570 e^{-5} s^2 + 3.420 e^{-11} s + 1.0330 e^{-11})}\right).$$  

(3)

Compared to a lower order transfer function a fourth order model is difficult to interpret. A straightforward model reduction did not reveal any pole-zero cancellations. Since the goal of this paper is to investigate the effect of emotion regulation within a data-driven model on the propagation of contagion, we did not attempt to further simplify the open loop transfer function.

Fig. 2. EEG data obtained from the literature [13]. Specifically, we extracted data from two experimental conditions, which is reprojected back onto the figure from [13] for verification. (Reproduced with permission from author)

B. Emotion Regulation as Closed-Loop Control

We model emotion regulation as a closed-loop proportional control [21] over the transfer function (3). The proportional control is of the form $G_c(s) = K_p$, where $K_p$ denotes the proportional gain and can be interpreted in terms of the cognitive effort exerted on the emotional response in order to attain a desired response level. We determined the value of $K_p = 0.23$ based on minimizing the root mean square error from the experimental data over a range of $K_p$ values between 2 and 4 with a resolution of 0.01 (Fig. 3). Modeled as a closed-loop system, emotion regulation is represented as a proportional controller that compares a desired emotional state to the current emotional state. In particular, $K_p$ can be seen as the cognitive effort that is exerted to check one’s emotional state based on the emotional response felt towards a situation. Although a linear controller is typically modeled as a proportional-integrative-derivative (PID) controller, we used a proportional controller only because it is the simplest form of feedback control that fit the experimental condition and it allows for the interpretation of results in light of a lack of clear understanding of the mechanisms behind emotion regulation.

Fig. 3. The data fit for open and closed-loop transfer functions in response to a step input. The blue vertical line denotes the 300 milliseconds position in time until which the data was ignored from analysis in [13] due transitions between instructional screens.
IV. RESPONSE OF A QUEUE OF EMOTIONAL AGENTS

To investigate the effect of emotion regulation on the spread of contagion, we simulate a line of $N$ agents, whose emotional state is represented by $e_i(t), i = 1, \ldots, N$. Each agent itself is represented by the closed loop transfer function $G_{cl}(s)$. Figure 4 shows a schematic representation.

Contagion is simulated by giving a step input to the first agent that lasts for 1 second. The output of the first agent is then input to the second agent, and the second agents output is input to the third agent, and so on. A delay of 0.25 seconds is added prior to sending the input to an agent. This delay corresponds to the average human reaction time to a visual stimulus [22]. A simulation is conducted for $N = 10$ agents. In the experimental data referenced in this study, as well as other studies that quantify response to fear using LPP, the response is typically bounded by 10 $\mu$V [23]. This indicates that the emotional state quantified by LPP is likely to have a ceiling effect. Accordingly, we constrain the absolute maximum of the response to lie within a range of [-10, 10] $\mu$V. Figure 5 shows the response of 10 such agents to a step input with the simulation run for 10 seconds, with the nominal values of the parameters $K_p = 0.25$.

We quantify the collective state of the simulated queue of emotional agents by normalizing the sum of absolute value of the states of all agents at time $t$. This is computed as $S_t = \frac{1}{N} \left( \sum_{i=1}^{N} |e_i(t)| \right)$. To compute the spread of contagion, we calculate the fraction of total number of agents above a threshold value of 5 $\mu$V. This value marks the rounded up maximum value that was measured for the distract-watch condition in the LPP data [13]. Finally, we compute the lead time as the amount of time it takes for 4 individuals to reach above the 5 $\mu$V threshold. This measure, where a high value is better, can for example relate to the lead time available before contagion spreads to 40% of the population, reaching a point of no return.

Figure 6a and 6b shows the value of $S_t$ and the fraction of individuals above 5 $\mu$V for different values of $K_p$. Note that $K_p = 0$ corresponds to an open-loop system. In Figure 6a, we find that $S_t$ rises and then oscillates around a high value with the open loop system response more than all closed loop responses. Figure 6b shows the number of agents above the threshold value of 5 $\mu$V with similar pattern, that is, open loop system showing more fraction of the population reaching the threshold value than closed loop systems.

The effect of proportional control $K_p$ is analyzed in Figure 7. Specifically, we vary the value of $K_p = [0, 0.5]$, where $K_p = 0$ indicates open-loop system, and $K_p = 0.25$ indicates the value closest to the one that fit the negative-distract data.

Our results show that the lead time is at a low value of 2.91 seconds for an open loop system. As $K_p$ increases to 0.25, the lead time further decreases to 2.80 seconds. For $K_p$ with a value of 0.3 to 0.5 the lead time increases dramatically reaching a high value of 3.48 seconds for $K_p = 0.35$. The dependence of $S_t$ and the number of individuals whose state is more than 5 $\mu$V during the 9th second shows that open loop system does worse than a closed system for all values of $K_p$, with the optimal value obtained at 0.25.

V. DISCUSSION

Emotion generation and regulation are complex processes whose mechanisms are not yet clear [24]. In this context, a linear ordinary differential equation may not provide the explanatory role of a detailed, nonlinear model [7]. At the
same time, simpler models can be calibrated easily using experimental data and can serve as a valid starting point for inclusion in complex scenarios. Importantly, the proposed approach is consistent with the literature on how emotions are checked [8], namely through a feedback loop. The resulting dynamical system modeling emotion generation however is different from appraisal based systems in that the feedback is not applied on the meaning attached to the stimulus [5], but instead on the emotional response. Therefore, closing the loop here implies that an individual tries to distract herself more if they find that their emotional response is not what they desire.

The data we used here for system identification represents an average across trials within a condition [13], and therefore it is expected that the individual differences will be present. However, the statistical comparisons in [13] show that the amplitudes of LPP signals are significantly different between experimental conditions in all of 200 milliseconds intervals between 300-1700 milliseconds. Therefore emotion regulation effects override individual differences and can be justified as modeled separately as is done in the form of a feedback loop here. In ongoing work, we are in the process of using raw data from the same experimental study to highlight such differences. In this context, future work will require simplifying the black-box model to identify the key similarities among individuals in terms of emotion generation and regulation. This may also require designing new experimental protocols with the aim of robust system identification.

Our results show that proportional control causes a reduction in the spread of contagion while being most effective at a value close to 0.23 that best fit the regulated response. This can be explained from a control systems perspective in that a high value of proportional gain, $K_p$, causes extensive overshoot. From a psychological perspective, $K_p$ could be interpreted in terms of the cognitive effort exerted by an individual to distract themselves from a negative stimulus by replacing anxiety related memories [16]. Accordingly a moderate effort is required to reduce the emotional state to a desired level potentially dangerous situation. To understand what causes overshoot in emotions, however, requires associating emotional state with LPP at a higher resolution by replacing anxiety related memories [16]. Accordingly a moderate effort is required to reduce the emotional state to a desired level potentially dangerous situation. To understand what causes overshoot in emotions, however, requires associating emotional state with LPP at a higher resolution by replacing anxiety related memories [16]. Accordingly a moderate effort is required to reduce the emotional state to a desired level potentially dangerous situation. To understand what causes overshoot in emotions, however, requires associating emotional state with LPP at a higher resolution by replacing anxiety related memories [16]. Accordingly a moderate effort is required to reduce the emotional state to a desired level potentially dangerous situation. To understand what causes overshoot in emotions, however, requires associating emotional state with LPP at a higher resolution by replacing anxiety related memories [16]. Accordingly a moderate effort is required to reduce the emotional state to a desired level potentially dangerous situation. To understand what causes overshoot in emotions, however, requires associating emotional state with LPP at a higher resolution by replacing anxiety related memories [16]. Accordingly a moderate effort is required to reduce the emotional state to a desired level potentially dangerous situation. To understand what causes overshoot in emotions, however, requires associating emotional state with LPP at a higher resolution by replacing anxiety related memories [16]. Accordingly a moderate effort is required to reduce the emotional state to a desired level potentially dangerous situation. To understand what causes overshoot in emotions, however, requires associating emotional state with LPP at a higher resolution by replacing anxiety related memories [16].

Relatedly, the model assumes that $K_p$ is constant and similar for all individuals, however this is likely not the case. This raises several questions in the context of emotional contagion itself: can a few individuals with optimal value of $K_p$ suppress the onset of contagion? Conversely, can few individuals with a high or low $K_p$ cause contagion? And finally, is there a distribution of $K_p$ values that are better suited for containing a wave of behavioral contagion? These questions will be addressed in detail as the framework is tested against more experimental data in future.

Although we consider a simple model of interaction between agents, there are several aspects of processing of stimulus, which may lend additional complexity to this interaction [25]. First, the delay of interaction may vary between individuals. Second, the presence of threatening stimuli may further inhibit the ability to generate a motor response [26], [27]. These different forms of interactions, along with extending the framework to a more realistic two-dimensional setup, will be systematically investigated in future work.

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REFERENCES
