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Integrating Valence and Arousal Within an Agent-Based Model of Emotion Contagion

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Abstract. Existing agent-based models of emotion contagion that account for the emotional diversity in groups have mostly focussed on the spread of categorical emotions (happy, sad, angry). In practice this raises problems with regard to how the spread of different emotions should interact. Can one be both very happy and very angry at the same time, or shift quickly between these states? And which emotion should determine the behaviour of an agent?

The present paper explores an alternative where dimensional emotions spread in a crowd and the emotional state of an agent equals its location in the valence-arousal space, corresponding to a single emotion. We propose an agent-based model that is an extension of the ASCRIBE model. Furthermore, building on recent work that found an attention bias in participants toward emotionally salient stimuli, we examine the effects of attention bias in the context of emotion contagion at the crowd level.

We have simulated a crowd in a soccer arena wherein several types of visitors react differently to the same events in the game (goals), with and without attention bias. Our results give a first indication that a dimensional approach to emotion contagion has the potential to solve these challenges without the need to model mood as an extra layer, though further study is required with regard to model validation and the translation from emotional state to behaviour in order to accurately simulate the complexity of real-world crowds that are emotionally diverse.

Keywords: Emotion contagion · Dimension theory · Attention bias · Agent-based model · Crowd simulation

1 Introduction

When a comedian tells a joke to a single listener this may evoke a different emotional response than when it is told in front of a packed theatre. The alignment of emotion at the group level is often called collective emotion. While in this example it can be assumed the members of the audience responded to the comedian, their emotion may also be affected directly by the emotions of other members of the audience, a phenomenon known as emotion contagion.

A growing number of studies over the past decade have used agent-based models to study the spread of emotion in large groups as the result of emotion contagion. They have focussed mainly on incidents where the safety of people in the crowd was in danger

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and emotion contagion caused or contributed to the collective behavioural response. Accordingly, the spread of a single negative emotion, usually either fear or anger, is studied most frequently in the crowd. However, studies have indicated that positive emotions also spread via contagion in groups [1, 2]. This raises the question whether emotional interaction between group members in many scenarios may be too complex to capture using a single emotion.

Indeed, several agent-based models have been proposed where multiple emotions spread via emotion contagion [3]. Most of these models investigate the contagion of categorical emotions, often based on the OCC model that distinguishes 22 emotions based on appraisal [4]. However, the spread of multiple categorical emotions allows for complex states where an agent experiences multiple and even seemingly contradictory emotions simultaneously. This poses a challenge in translating such a state to a behavioural response of the agent and the contagion process among agents. Does the strongest emotion determine the behaviour and is this therefore the only emotion that is contagious, or do all emotions affect behaviour and the contagion process? And can a person experience high levels of two (opposite) emotions simultaneously?

A solution proposed by several studies is to use the Pleasure-Arousal-Dominance model to simulate the mood of an agent along three continuous axes [5, 6]. In this setup, mood acts like an intermediary between the emotions and behaviour of an agent. Emotion is mapped to affect the mood of the agent slightly and in turn affects the behaviour of the agent, thereby preventing erratic behaviour from fast changes in emotion.

In the present paper we propose a more parsimonious alternative by modelling emotions directly along two continuous axes, valence and arousal, based on the circumplex model of emotion [7]. The emotional state of an agent equates to a single location in this two-dimensional space. Areas in this space are labelled as a type of emotion to facilitate human interpretation, thus resulting in a single emotion label for the state of an agent at any time. For this purpose, the ASCRIBE model [8], an often used model of emotion contagion that is agent-based, was extended for valence and arousal to spread simultaneously and independently among agents. The ASCRIBE model was chosen because contrary to epidemiological-based models, it considers contagion on a continuous scale [3]. Also, it has been validated using footage of real crowds and was found to compare favourably in relation to several other models of emotion contagion.

Our aim is to investigate the dynamics of the proposed model and test whether it remedies the problems encountered with categorical emotions. For this purpose, we simulate a crowd in a soccer arena wherein several types of visitors react differently to the same events in the game (goals) and multiple emotions spread among the stationary agents. We expect that the transitions in the emotion state of an agent due to contagion occur gradually, where an agent under the influence of others with an opposite emotional state first becomes less emotional or transitions to an emotional state that is nearby its original state.

Furthermore, in a recent publication Goldenberg et al. (2020) let participants estimate the emotion of the crowd and found that this estimation was biased towards others with stronger facial expressions, thus resulting in a skewed assessment in the presence of strong emotions [9]. We hypothesize that if observing emotions triggers an emotional response and this observation is an overestimation, this results in amplification at the group level of the strongest emotions in the crowd. Therefore, in the present paper we also investigate the effect of an attention bias towards agents with a strong expression of emotion.

2 Methods

2.1 Emotion Contagion in the ASCRIBE Model

With the ASCRIBE model the authors considered the spread of a single categorical emotion among agents [8]. Emotion is expressed as a continuous number between 0 and 1, where 0 represents the lowest level or absence and 1 the highest level of emotion. The contagion process is divided in two aspects, 1) the emotion channel through which emotion flows and 2) the potential emotional influence the sender has on the receiver.

The first aspect, the width of the emotion channel, is determined by the personality of the agents that are involved and the social or physical distance between them. The second aspect, the influence the emotional expression of the sender has on the receiver in ASCRIBE, is determined by a blend of two processes: absorption and amplification. Absorption represents the tendency for the receiving agent to adjust its emotion to its surroundings. When considering only absorption in a group, over time the emotions of its members approach each other and eventually reach an equilibrium, the value of which always lays within the range of emotion that was present at the start. Amplification, despite its name, represents the ability for emotional escalation or de-escalation of the emotion of the receiver when its emotion matches that of its surrounding. Whether the amplification process escalates or deescalates emotion or behaves similar to absorption is determined by a characteristic of the receiving agent. Note that amplification can therefore result in collective emotion beyond the emotional range that was present at the start, providing the ability to simulate emotional spirals like a spontaneous outbreak of panic in a crowd due to emotion contagion.

2.2 The Proposed Model

In the present paper we extend the ASCRIBE model and propose a model for emotion contagion in two dimensions of emotion, namely valence and arousal. Different from ASCRIBE, both dimensions range from strongly negative at -1 to strongly positive at 1, where 0 represents a neutral state. Contagion of valence and arousal occurs simultaneously and independently among agents.

The change in valence and arousal of an agent (ΔE_r) due to contagion is the result of the total connection strength between the receiver and its neighbours, times the emotional influence for that dimension of emotion.

$$\begin{aligned} \Delta E_{r_{valence}} &= \langle connection \rangle * \langle influence_{valence} \rangle \\ \Delta E_{r_{arousal}} &= \langle connection \rangle * \langle influence_{arousal} \rangle \end{aligned} \quad (1)$$

Connection Strength. How much of the emotional influence can flow from the senders to the receiver is determined by the strength of the connection between each sender and the receiver. We assume that there is only one channel between a receiver and a sender.

Therefore, the connection strength influences contagion of valence and arousal equally. The total connection strength (Γ_r) between a receiver and its neighbours is given by the sum of the individual connection strengths between the receiving agent and each of the senders (γ_{sr}) in the group Nr.

$$connection = \Gamma_r = \sum\nolimits_{s \in N_r} \gamma_{sr} \tag{2}$$

The strength of the connection between two agents (γ_{sr}), a sender and a receiver, is determined by three components. The first is the personality characteristic openness (δ_r) of the receiver that represents the tendency to take up affective information. The second is the channel strength between both agents (α_{sr}), which in the present paper is defined as the inverse distance between the agents in space. Last is the weighted attention (θ_s^*) of the receiver for the sender. We assume that an agent has a limited amount of attention and distributes this among its neighbours [10]. The weighted attention (θ_s^*) represents the share of attention a sender claims in the context of competition.

$$\gamma_{sr} = \theta_s^* \alpha_{sr} \delta_r \tag{3}$$

To calculate the weighted attention θ_s^* for a sender, we take the potential attention (θ_s) the sender could receive plus a basic level of attention every sender receives (1/N) and weigh this to that of all senders in group N_r. The relative importance of the potential attention (θ_s) is determined by the constant κ_1, that is set to 1 in the present paper.

$$\theta_s^* = \frac{\frac{1}{N} + \kappa_1 \theta_s}{1 + \kappa_1 \sum\nolimits_{c \in N_r} \theta_c} \tag{4}$$

Without a bias in attention towards emotional stimuli, the potential attention (θ_s) a sender claims is equal to the personality characteristic expressiveness (ε_s) of the sender, that represents its tendency to show or voice its affective state.

$$\theta_s = \varepsilon_s \tag{5}$$

Emotional Influence. The emotional pressure from a group of neighbours on a receiver is determined by the nett emotion the receiver observes and the tendency of the receiver to dampen, absorb or amplify this perceived nett emotion. Note that the term emotion here can be replaced by either valence or arousal that are calculated independently. To get the nett emotion (E_s^*) of the group of senders (N_r) as observed by the receiver, the emotion of each sender is weighed by the channel strength of the sender (γ_{sr}) against the overall channel strength (Γ_r) of the group.

$$E_s^* = \sum\nolimits_{s \in N_r} \frac{\gamma_{sr} E_s}{\Gamma_r} \tag{6}$$

In ASCRIBE the tendency of the receiver to amplify or absorb was based on two separate processes, the balance of which was set via two parameters. However, because the amplification process in ASCRIBE can mimic the result of the absorption process with the setting of a single parameter (see appendix 1 for an example), in the proposed model we simplified the emotional influence to one process based on the amplification process in ASCRIBE. In the proposed model, one characteristic of the receiver determines the tendency of a receiver to dampen ($\beta_r < 0.5$), absorb ($\beta_r = 0.5$) or amplify ($\beta_r > 0.5$) the emotions of its neighbours. To accommodate for the extended range of emotion in the proposed model (from -1 to 1), the total emotional influence of the senders on the receiver is calculated differently depending on three conditions. First, when both the emotion of the receiver (E_r) and the weighted average of the senders (E_s^*) is on the positive side of the scale, the influence is calculated in the same manner as the amplification process was in ASCRIBE. Second, if both the receiver and the average of its neighbours are on the negative end of the scale, influence is calculated like in ASCRIBE and then inverted. Lastly, when the receiver and its neighbours have an opposite polarity, the emotion is the difference between the weighted emotion of the senders modulated by β_r and the emotion of the receiver modulated by $1 - \beta_r$.

$$\begin{aligned}
&IF(E_s^* \geq 0)\&(E_r \geq 0)\\
&\quad influence = \beta_r(1 - 1(-|E_s^*|)(1 - |E_r|)) + (1 - \beta_r)E_s^* E_r - E_r\\
&ELSE\ IF(E_s^* \leq 0)\&(E_r \leq 0)\\
&\quad influence = -(\beta_r(1 - (1 - |E_s^*|)(1 - |E_r|)) + (1 - \beta_r)E_s^* E_r) - E_r\\
&ELSE\\
&\quad influence = \beta_r * E_s^* - (1 - \beta_r) * E_r
\end{aligned} \tag{7}$$

Figure 1 shows the emotional influence for different levels of emotion of the receiver and its neighbours for three levels of characteristic β_r of the receiver. The lower-left and upper-right quadrants show that the reaction of a receiver to neighbours with the same emotion polarity depends on the setting of β_r. A positive β_r amplifies the emotion of the receiver (towards 1 or -1 depending on the polarity), a neutral β_r pulls the emotion of the receiver towards that of the senders (absorption), and a negative β_r dampens the emotion of the receiver (towards 0). The upper-left and lower-right quadrants show the scenarios where the polarity of emotion differs between the receiver and senders. In this case the emotion of the receiver is pulled towards that of the senders, the rate of which is determined by β_r. Note that the amount of influence that can flow towards the receiver is determined by the connection strength as shown in Eq. 1.

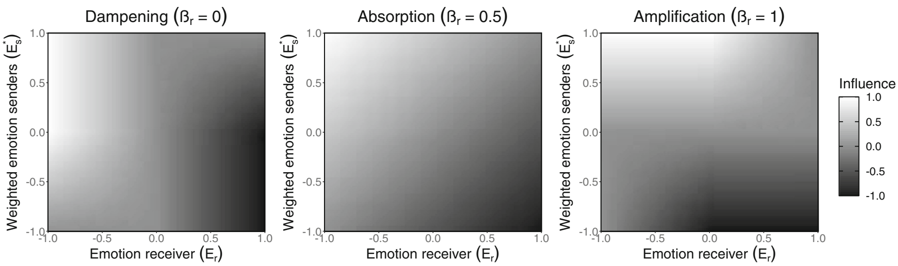

Fig. 1. Emotional influence as a function of the emotion of the receiving agent and the weighted emotion of the senders, shown for three levels of characteristic β_r.

Bias Towards Salient Emotional Stimuli. Judging the emotional state of a crowd requires fast evaluation of many stimuli, while people are generally assumed to have a limited capacity to do so. In recent work, Goldenberg et al. performed an experiment in which participants had to judge the average emotion of a set of faces with varying emotional expressions on a monitor [9]. The authors found that people overestimated the average emotion in a crowd, especially when this emotion was negative, and did so increasingly with a larger crowd and longer exposure time.

Then to explore what mechanism underlies this overestimation, Goldenberg and colleagues tracked the eye movement of the participants and found that emotional expression of a face did not affect whether a face was examined by the participant. Yet, when considering the dwell time, the duration with which a participant examined each face was found to be correlated with the strength of the emotional expression on the face. Moreover, the estimation error increased rather than decreased with the number of presented faces and longer exposure time to the faces. According to the authors, this hints at a preference in attention for faces that express strong emotions, rather than a selection bias for expressive faces due to constraints in how many faces could be processed in the given time.

Following these findings, we investigate the effect of attention bias on the spread of emotions in the crowd. We implemented a bias towards emotional salient stimuli in the proposed model via the potential attention (θ_s) a sender receives, replacing Eq. 5. The potential attention θ_s an agent receives is determined by both the expressiveness of the sender (ε_s) and its emotional state (E_d). To determine a single value for the potential attention of a sender over multiple dimensions of emotion (here dim = {valence, arousal}), we calculate the distance towards the neutral state of zero. To model a preference of the receiver for negative or positive stimuli two components are added, the balance between which is set by parameter μ_r, where $\mu_r < 0.5$ represents a preference towards negative emotions and $\mu_r > 0.5$ towards positive emotions.

$$\theta_s = \sum\nolimits_{d \in dim} \left(|E_d| * \varepsilon_s + \mu_r * \left(2 - \frac{E_d + 1}{2} \right) + (1 - \mu_r) * \left(\frac{E_d + 1}{2} \right) \right)^2 \quad (8)$$

The result of attention bias is that a larger share of the attention goes to agents with a stronger expression of emotion, yet all agents receive a basic level of attention and no agents are ignored by the receiver (Fig. 2). This description corresponds to the findings by Goldenberg et al. [9] where participants examined all faces presented to them, but looked longer at those that were more emotional, and did more so when that emotion was negative than if it was positive. To simulate this preference for negative stimuli over positive stimuli, we set μ_r to 0.4 for all simulations in the present paper.

Emotional Self-regulation. In the absence of emotional stimuli (either internal or external), emotion in a person does not persist, nor does the emotion vanish immediately. Instead, emotion is thought to decay over time with a certain speed and in a non-linear fashion that varies among people and types of emotion [11].

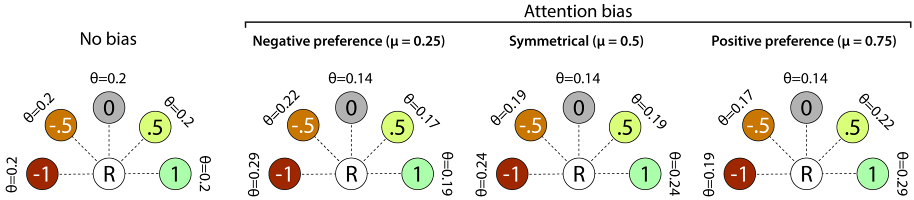

Fig. 2. Effect of attention bias in the distribution of attention of receiver R towards a group of senders (surrounding circles) for three preferences of stimuli type (μ_r). For simplicity only one dimension of emotion is shown. The emotions of the senders are indicated in the circles and the attention (θ_s) that the sender receives is indicated outside of the circle. In this example all senders have the same expressiveness ε_s set to 0.5.

In the proposed model, an agent can become less emotional, i.e. closer to the zero point on the axes of valence and arousal, when it meets others with an opposite emotion or via dampening ($\beta_r < 0.5$). Yet based on these processes, when an agent would not meet other agents, it would maintain its level of emotion indefinitely. Hence, we have added a function of emotion decay to the proposed model. According to Hudlicka [11] an exponential or logarithmic decline is more realistic than a linear decline for emotional decay. Therefore, we chose a logit function, as this is similar to an exponential relation that is mirrored in the negative direction to account for the decay of negative valence and arousal.

Preceding the contagion process, the emotion of the receiver is reduced depending on the decay rate λ_r of the receiver and its current level of emotion (E_r). A higher λ_r results in a faster decay of emotion, while at a decay rate of zero there is no decay of emotions (See appendix 2 for an example). The constant κ_2 sets the curve of the line, where a value approaching one results in a more curved line while a value approaching infinity results in a line that is approx. linear. In the present paper κ_2 was set to 1.1.

$$\Delta E_r = -\lambda_r * \log \frac{\frac{1}{2}\left(1 + \frac{E_r}{\kappa_2}\right)}{1 - \frac{1}{2}\left(1 + \frac{E_r}{\kappa_2}\right)} \tag{9}$$

Mapping to Categorical Emotions. To improve human interpretability of the results, locations in the valence and arousal space are commonly mapped to categorical emotions. However, currently there exists no clear consensus about how indicative the dimensions of valence and arousal are for specific categorical emotions, nor a generally agreed upon model of how continuously measured emotion should be translated to emotion labels that are used in everyday life.

As a starting point, we have chosen eight emotions and a neutral state that are equally separated in the valence-arousal space and we estimate to be relevant in the context of crowd management. Figure 3 shows the area that is associated with these emotions. The locations of the emotion labels are a simplification of the space described by [12].

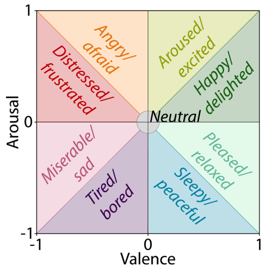

Fig. 3. Mapping of the valence-arousal space to emotion labels.

3 Results

To study the spread of continuous emotion in an emotion-rich environment, we simulated a soccer match that is visited by 2900 agents in an arena. The agents respond emotionally to the events on the field, specifically to a goal for the home team after 50 steps and a goal for the away team after 500 steps. How an agent responds to these events depends on what type of visitor the agent is. Agents with the same type are placed together in sections of the arena inspired by the arrangement in some Dutch soccer arenas (Fig. 4). There are three types of agents that support the home team. The valence of these agents increases when the home team scores and decreases when the away team scores, where the family-type agents respond mildly, regular supporters at an intermediate level and fanatic supporters respond strongly (Table 1). For the away team we assume mostly the highly motivated fans travelled to support their team and thus behave similarly to the fanatic supporter except the valence reaction is reversed to the home and away goal. Arousal increases for all agents after each goal, where family-type agents stay relatively calm, regular supporters get somewhat excited and the fanatic and away supporters become most excited. Lastly the family-type agents have a tendency to absorb emotion, thereby adjusting to their environment, while regular and to a higher degree fanatic and away supporters have the tendency to amplify emotional stimuli when they match their own emotion.

Since the simulations did not contain any stochastic elements, one run was performed per condition. Each simulation was run for 1000 timesteps, recording the levels of valence and arousal of every agent. To focus on the contagion mechanism, behaviour was not considered. See Appendix 3 for a complete list of parameter settings.

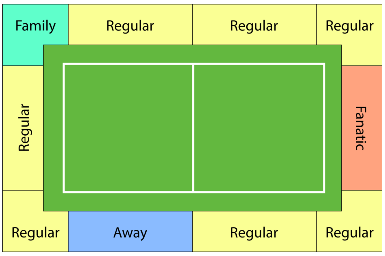

Fig. 4. Distribution of agent types over sections of the soccer arena.

Table 1. Parameter settings for agent types

Agent type	N	β_r	Response home goal		Response away goal	
			E_{val}	E_{aro}	E_{val}	E_{aro}
Regular	2000	0.6	0.3	0.3	−0.3	0.3
Fanatic	330	0.7	0.5	0.5	−0.5	0.5
Family	240	0.5	0.3	0.1	−0.1	0.1
Away	330	0.7	−0.5	0.5	0.5	0.5

3.1 Contagion in a Multi-emotion Environment

To first investigate the contagion of continuous emotions, Fig. 5 shows the results of a run without an attention bias. At the start of the run, all agents have a neutral emotional state and no contagion takes place until an event (goal) evokes an emotional response in all agents at step 50. After this step only contagion and decay affect the emotions of the agents until the second event at step 500.

Several differences can be observed among the types of agents in Fig. 5B, not only in the one-step response to the event, but also in the contagion and decay process that follows. The family-type agents react mildly happy/delighted to the events and afterwards their emotional response quickly fades. This happens because these agents have the tendency to absorb instead of strengthen similar emotions and the emotional influence of the surrounding supporters is less than the decay due to self-regulation. Their emotion however does impact the regular supporters that are close, who become less aroused and change from aroused/excited to happy/delighted.

In contrast, the fanatic- and away-type of agents respond strongly to the events and, while there is some decay after the initial emotional stimulus, these supporters amplify each other enough to compensate for emotion decay, finding an equilibrium. Notable is the difference between the fanatic and away supporters in the response to the (to them) negative event. While their initial emotion response is the same, the valence of the away supporters is reduced stronger (towards 0) due to contagion than in the fanatic supporters. This is because both groups are bordered by the regular supporters that express a similar though less extreme sentiment to the fanatic supporters while contrasting the away supporters. This also effects the regular supporters, as can be seen in Fig. 5A, where at step 150 and 600 in the areas where the away and regular supporters border the emotion of some regular agents was extinguished and those closest to the away group adopted the emotion of the away group, though to a lesser degree. Oppositely, at the border between the fanatic and regular supporters the emotion of the regular supporters is stronger compared to other regular supporters.

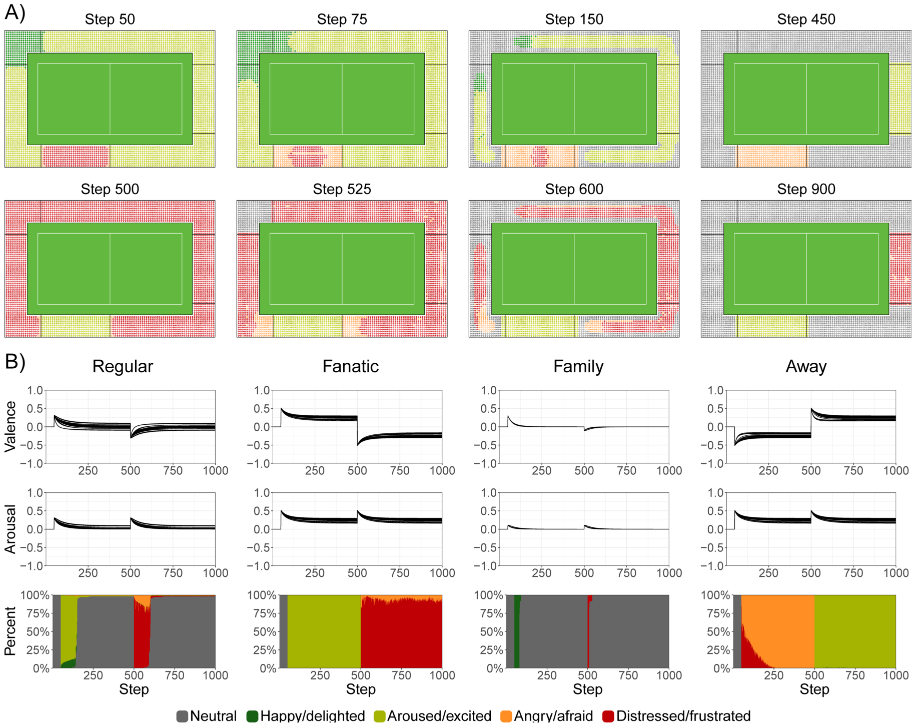

Fig. 5. Simulation of visitors to a soccer game without attention bias. A) Illustration of the spread of emotions among agents over time. Note that the colours correspond to Fig. 3 and do not express the strength of the emotion. B) Development of emotion over time per agent-type, shown as a line per agent for valence and arousal and as the percentage of agents with an emotion label.

3.2 Attention Bias Towards Emotional Salient Stimuli

Next, to study the effect of an attention bias in the context of emotion contagion in a crowd, Fig. 6 shows the results of the same experiment as before but with attention bias. Comparing Fig. 5 to Fig. 6, it can be observed that there is amplification of the agents that express strong emotions (fanatic & away supporters), with less decay of emotion and less influence of the bordering agent type (regular supporters). The regular supporters are influenced more strongly by the fanatic and away supporters with attention bias enabled (see for example the larger group of regular supporters that adopts the sentiment of the away supporters). The family-type supporters do not express strong emotions, yet still impact the emotions of nearby regular supporters. This most likely is because each sender always receives a basic share of attention and, as both family and regular supporters do not express strong emotions, the impact of attention bias is relatively small.

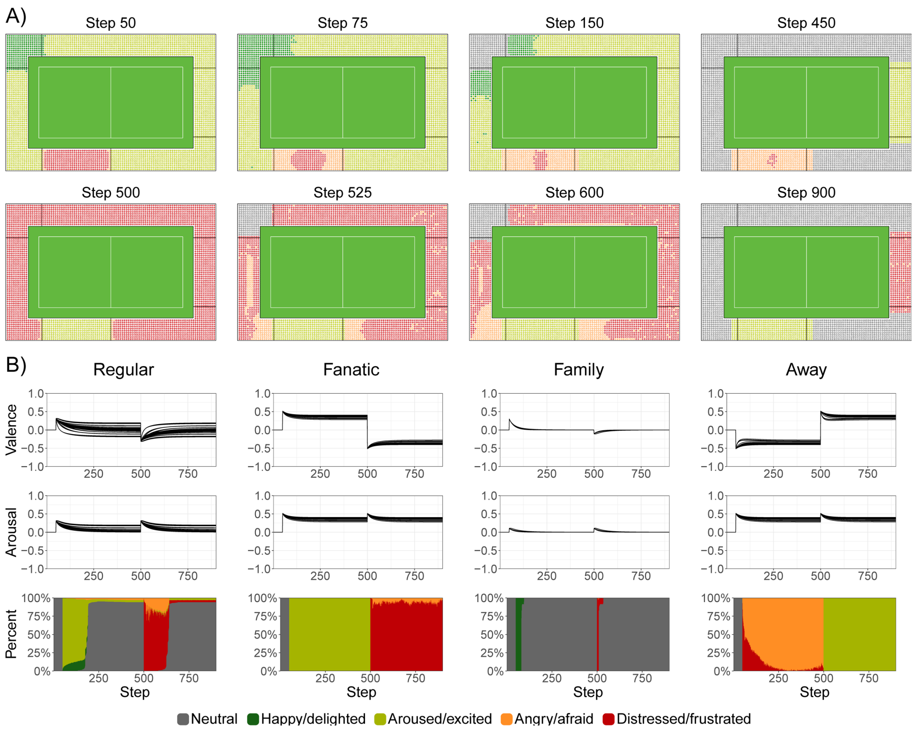

Fig. 6. Simulation of visitors to a soccer game with attention bias.

4 Discussion

With the present paper we took a dimensional approach to the spread of emotions in large groups, where valence and arousal spread independently yet together represented the emotional state of an agent. The location in valence-arousal space was mapped to a categorical emotion label to make the results more interpretable for humans.

Our results demonstrate that a dimensional approach to emotion contagion has the potential to solve problems arising from the contagion of multiple categorical emotions without the need to model mood as an extra layer. Because the dimensional emotions spread independently but together form a single emotional state, this results in more stable transitions of emotion over time. Although we do not model mood explicitly, it can be argued that mood is an emergent property that arises from the tendency to keep the same emotional state in the proposed model (e.g., frustrated) or shift to a nearby state following emotional input (angry), instead of an emotion that is distant in the valence-arousal space (peaceful). Important to note is that while mapping the multi-dimensional space to categorical emotion labels makes the results easier to interpret for humans, currently there exists no consensus on what dimensions of emotion should be considered and what the exact locations are of emotion labels in the space these dimensions form. Future work may therefore also consider exploring additional or alternative dimensions of emotion in the context of contagion. The dimension of dominance for example has frequently been considered in addition to valence and arousal in recent work. We believe that the proposed model offers a suitable starting point for this as dimensions of emotion can easily be replaced or added and the mapping used in the present paper can be refined to more precise areas in the chosen emotion space.

Further, we examined the effect of a bias of agents towards emotionally salient stimuli in the contagion process and found that such a bias amplifies the strongest emotion in surrounding agents, yet does have a large impact on the contagion process in an environment that is emotionally poor or homogeneous. This kind of amplification may be of importance in scenarios where one or some members of the crowd strongly deviate from the general sentiment, for example in the case of a sudden calamity or aggression or when considering an entertainer or leader.

Future work will be aimed at validation of the model in groups and the translation of emotional states to behaviour of the agent in an attempt to realistically simulate the complexity of real-world crowds that are emotionally diverse.

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Appendix

The supplementary material can be found at: osf.io/vt7c6.

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