A Model for Emotional Contagion Based on the Emotional Contagion Scale

João Bispo
UTL/IST
Av. Rovisco Pais, 1, 1049-001 Lisboa
joaobispo@gmail.com

Ana Paiva
INESC-ID and IST
Av. Prof. Cavaco Silva, Porto Salvo, Portugal
Ana.paiva@inesc-id.pt

Abstract

Emotional contagion is a process by which a person or group induces emotions, consciously or unconsciously, to another person. In this work, the authors present a model for contagion of emotions using the Emotional Contagion Scale (ECS). The model focuses on the unconscious aspect of Emotional Contagion, and is implemented using the NetLogo environment. The results show that the model can simulate different contagious patterns according to different emotions and different sizes of the groups, simulating what is found in human groups.

1. Introduction

Emotional contagion is a powerful agent in setting the mood in a group in a variety of situations [1, 2]. It is a mechanism which has both conscious and unconscious parts, and there are still innumerous aspects of this process that need to be investigated. Even though, there is already evidence that we are automatically and constantly affecting and being affected by others' emotions at a surprisingly fast rate [3]. For that reason, recent studies have focused on this automatic part of the mechanism, which passes unnoticed by most people as it seems to work mostly at an unconscious level. However, can these automatic mechanisms account for the most part of the behavior we identify as emotional contagion? And are these mechanisms rich enough to generate a believable behavior of simulated agents with emotional contagion?

In this work we propose a model for emotional contagion which only takes into account the automatic processes, also known as Primitive Emotional Contagion [3]. The scenario for the model will consist in a group of agents, each one talking in turns (Figure 1). The size of the group is a parameter, and strategies could be assigned as how the agents will talk (each one can talk in order, a specific individual can have more talk time than others, or it can be completely random). In this work, agents will talk randomly. Each time some agent talks (a "transmitter), every other agent (a "receiver") may be affected by the predominant emotion of the talker (the "current emotion"). Additionally, we want to account for an observed behavior related to sadness-like emotions [4].

The aim is to create groups of agents where the emotional contagion process is believable and similar to the one found in humans. By obtaining such model, we expect to be able to use it in application areas as different as traffic models, simulation of panic situations in public spaces, or even computer games with groups and societies of emotional agents.

This paper is organised as follows. Section 2 explains the concept of Emotional Contagion; what is known about the automatic process of contagion and introduces the Emotion Contagion Scale (ECS), which was used in our model. Section 3 describes in detail the model for Emotional Contagion. Section 4 presents the implementation of the model in the environment NetLogo, and Section 5 concludes the paper.

2. Emotional Contagion

Emotional contagion is a "process, by which a person or group induces emotions, consciously or unconsciously, to another person" [5].

There is not a clear definition of what an emotion is, but there is a consensus about some aspects of the affective phenomena. Most importantly, each affective construct of emotion can be associated to a specific intensity and time frame. We can consider three basic types of affective experiences: emotions, moods and dispositional affect [1]. In this view, emotions are defined as subjective experiences, which can last from seconds to hours [6]. Differently, moods last longer than emotions, and are less intense and perhaps more diffuse. Lazarus describes moods as "a transient reaction to specific encounters with the environment, one that comes and goes depending on particular conditions" [7]. Further, dispositional affect is a stable, long-term variable [8] which is not likely to be influenced by emotional contagion, but can influence it.

Emotional contagion has been studied in the past [9] by many researchers, and some authors have studied its role and processes by creating field studies about mood convergence in work teams [10-12]. Such works implied a causal process of emotional contagion in groups, which was established in [1]. Indeed, there is evidence that people continuously influence and are influenced by the others' emotions without even realizing it [3]. This supports the idea that we will pursue in this paper, that the process of emotional contagion that is mostly unconscious.

2.1. Automatic Emotional Contagion

One fundamental work in emotional contagion was developed by Hatfield *et al.* [3] where they provide evidence for Primitive Emotional Contagion as a strong contributor for emotional contagion. Primitive Emotional Contagion can be defined as “the tendency to automatically mimic and synchronize expressions, vocalizations, postures, and movements with those of another person's and, consequently, to converge emotionally” [13]. Hatfield *et al.* make three propositions to explain the mechanism of emotional contagion, taking only into account Primitive Emotional Contagion:

1) In conversation, people automatically and continuously mimic and also synchronize their movements with the facial expressions, voices, postures, movements, and other instrumental behaviors of others.

2) Subjective emotional experience is affected, moment-to-moment by the activation and/or feedback from facial, vocal, postural, and movement mimicry.

3) Consequently, “people tend, from moment-to-moment, to catch others’ emotions”.

Barsade [1] further explores the influence of emotional contagion in groups, and studies how two factors affect the process of emotional contagion: the valence of the emotion (which can be positive or negative) and the energy with which the emotion is expressed. Barsade uses the terms valence and energy as they are used in the circumplex model of emotions, where emotions are classified in a 2-D plane of valence-energy [14]. Further, he hypothesizes that unpleasant emotions are more likely to lead to mood contagion than are pleasant emotions (thus a dependence on the valence), and that the same emotional valence expressed with high energy will lead to more contagion than if expressed with low energy. Yet, neither hypothesis was supported by the studies carried. However, the data suggests that people who suffer from low-energy, unpleasant mood (depression, sadness) are less prone to be influenced by mood contagion.

Wild *et al.* [15] builds on the work of Hatfield [16], studing emotional contagion specifically through facial expressions. Their findings support the hypothesis that emotional contagion through facial expressions happens too fast to be a conscious process, and that the contagion is not only stable but repeatable. During the experiments, the subjects feel the emotions momentarely, and the authors explain these emotions as a mixture of the following:

1) An emotion corresponding to the emotion depicted in the facial expression, transmitted by Primitive Emotional Contagion.

2) An emotion evoked by the current situation.

3) An influence by the disposicional affect of the individual.

Wild also found evidence that after contagion, stronger expressions evoke stronger emotions, but could not relate it to a stronger probability of contagion.

Sy *et al.* suggest that a leader has greater chances to influence others’ emotions in part because it gets more attention than other people from a group[17].

A different study from Safran [4] among elementary school children found that low-energy emotions, such as sadness, can still influence the mood of others, but were rated as the least contagious of all behaviors in the classroom, and also one of the more difficult to change.

2.2. Emotional Contagion Scale

A problematic issue for the model was how to generate a population of agents that approximates a real population, to create behaviors adequate to a process of emotional contagion. Doherty [18] presents the Emotional Contagion Scale (ECS) that measures the individual susceptibility to emotional contagion, across five different basic emotions (Love, Happiness, Fear, Anger, and Sadness). The score is calculated using a 15-item questionnaire, and the scale is a five-point Likert scale, which has the options Never, Rarely, Usually, Often, and Always. After the questionnaire, each emotion has a score, represented by a real number between 1 and 5, being 1, Never, and 5, Always. This scale was validated, and already been used to evaluate emotion contagion susceptibility [19-21]. As such, it seemed adequate to use as a starting point for a computational model of emotion contagion.

3. An Emotion Contagion Model

As in [1], in this work we will consider the visible effects of emotional contagion to occur at the level of mood contagion.

Figure 2 shows how an agent is modeled. Each agent has a set of variables to record the current score for each emotion. The higher the score, the more likely that will be the emotion that will be expressed. This set of variables was labeled “Current Mood”. Each time the agent is influenced by an emotion, the value of variable corresponding to that emotion raises, while the values of others emotion lower. The predominant emotion of the “Current Mood” is calculated by using the values in that set of variables.

In the current implementation of this model, the following choices were made. Calculation of the predominant emotion is done by choosing the emotion which has the highest score in the set of variables of “Current Mood”. If two or more emotions have the same value, the emotion which comes first is chosen, in the same order as in Table 1. The variables in “Current Mood” are altered in such a way that summing the values of all Current Emotions in an individual will always be 0. Finally, there is a limit for the top value of an emotion variable, but there is no limit for how low it can be.

The ECS score can be seen as a probability of being affected by others’ emotions. Because it is an ordinal scale, the size of the interval between each of the five answers is not necessarily equal, and the probability associated to each answer will always be arbitrary.

Because the values of the ECS will be a real number between 1 and 5, for the sake of simplicity, in the model we will treat the ECS score as an interval scale, where 1 (Never) corresponds to 0% and 5 (Always) corresponds to 100%.

Another variable is the Emotional Status. It represents the dispositional affect of the individual, before coming to the group. This variable corresponds to one of the emotions of ECS and is randomly assigned to each agent at setup time. Its value remains unchanged during the execution of the model. At setup time, this variable will set the Current Mood, and when the model executes, it will affect the Current Mood every time the agent does not suffer Emotional Contagion.

Finally, each agent has an ECS score for each emotion, and this is what determines the probability of contagion, for that specific agent. The ECS score is a real number between 1 and 5 and in this work corresponds linearly to a 0%-100% scale. The values of the ECS score for each agent are calculated by calculating random values from a normal distribution. Each emotion has a different distribution, and the values of the mean and the standard deviation in Table 1 are taken from data of field studies. In this work the values were taken from the work of Lundqvist [22], and correspond well with previous findings for the ECS.

To account for the special case of sadness [1], the model has variables to adjust the probability of contagion in relation to the level of "energy" [14] of the current emotion of a receiver (in this implementation, the value associated with each kind of energy is multiplied by the original probability). It wasn't found a relation between a low-energy emotion in the transmitter and less contagion, but it is suggested that a receiver with a predominant low-energy emotion will be less susceptible to contagion. Table 1 shows what type energy corresponds to each emotion. The relations between which energy level correspond to each emotion are fixed in the model, and were inspired by Russell's work [14]. The values for each variable in the Energy column of Table 1 are arbitrary and parameters of the model.

Emotion	Energy	ECS Mean, (SD)
Happiness	Neutral	4.0 (0.6)
Love	High	4.0 (0.7)
Anger	High	3.5 (0.7)
Fear	High	3.1 (0.8)
Sadness	Low	3.4 (0.8)

Table 1: Relation between emotions and energy.

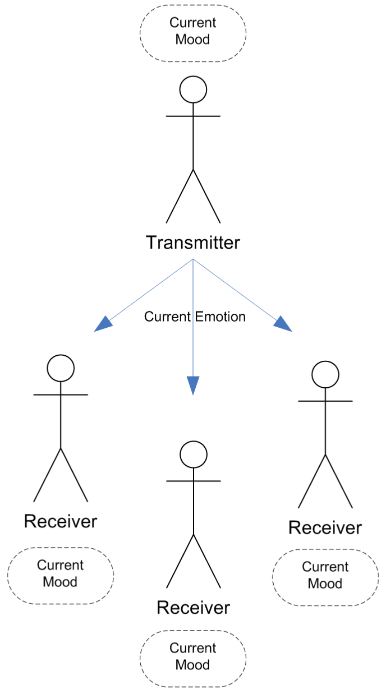

Figure 1: General View of the Model.

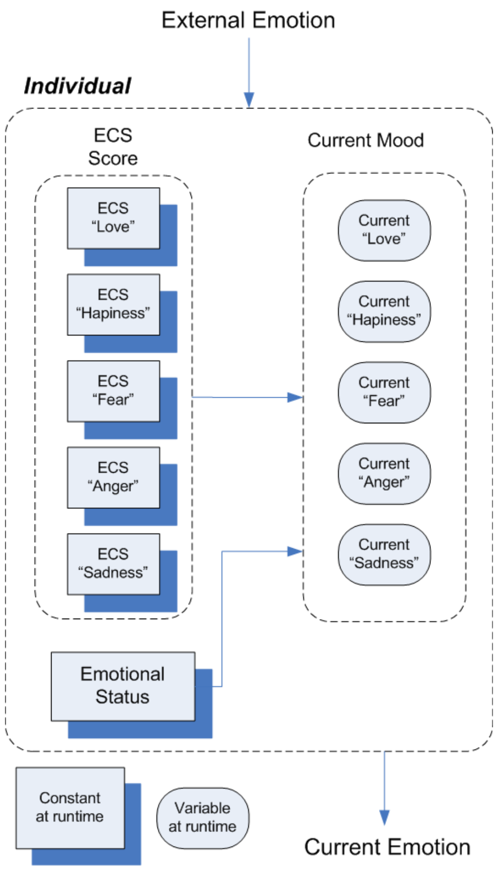

Figure 2: Model of a single Agent.

3.1. How the Model works

In Figure 1 a general view of the model is presented. When an agent (Receiver) listens to who is talking (Transmitter), it may become affected by the transmitter's current emotion. The probability of being affected is given by the ECS score. If an individual is affected, its current mood is modified, although its current emotion might not be. If the individual is affected by the external emotion, the variables in the current mood are adjusted. The *currentEmotion* which corresponds to the external emotion is modified according to equation (1), while all other emotions are modified as in equation (2) *emotionStep* is an arbitrary value, which in this work is set to 1, while the number of emotions in this case is five, the number of ECS emotions.

If the agent was not affected, the variables in the current mood are adjusted as if it was affected by an external emotion equal to the individual's Emotional Status.

After that, we calculate the predominant emotion of the current mood, and check if it changed. In this work,

```
newCurrentEmotion = currentEmotion +
(emotionStep x (numberOfEmotions - 1))
```
(1)

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newCurrentEmotion = currentEmotion -
emotionStep
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(2)

the predominant emotion is calculated by finding the emotion that corresponds to the maximum value in the "Current Mood" set of variables.

Stronger expression of emotions [15] is not directly supported in the model, but can be simulated by giving to a specific agent more chances to talk [17].

4. The NetLogo Model

The model for emotional contagion was implemented using NetLogo, an environment for multi-agent programmable modeling [23]. The model implemented in NetLogo has six parameters: *group-size*, *max-emotion*, *low-energy*, *neutral-energy*, *high-energy* and *num-ticks*.

Group-size sets the number of agents in the model. *Max-emotion* determines the maximum value each variable in current mood can reach, before becoming saturated. After an emotion reaches its maximum value, until it gets a lower value it is no longer affected by emotional contagion. *Low-energy*, *neutral-energy*, *high-energy* are floating-point numbers and are the values for the set of variables in the *energy* column in Table 1. *Num-ticks* defines how many steps a run of the model will have.

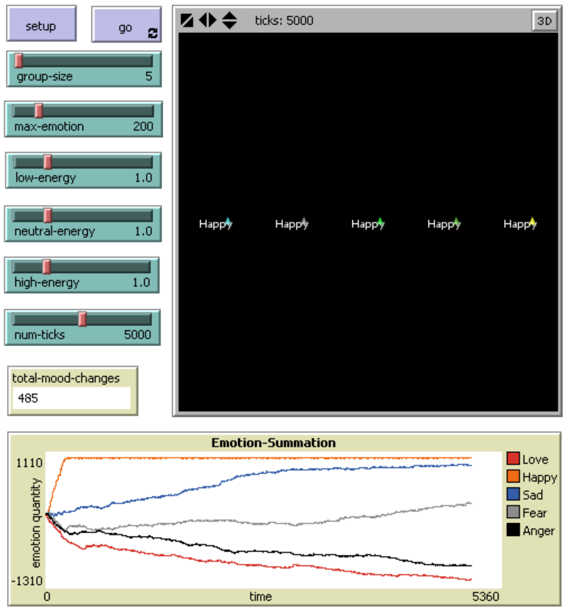

Figure 3: NetLogo Model

4.1. Characterization of the NetLogo Model

In order to test the model we have explored the various parameters, in a series of experiments. In all experiments, the parameter *num-ticks* was fixed at 5000 steps. This simulation time was enough to study the behavior of the model for all cases. Emotions are equally distributed at setup time, and at the beginning of the simulation, the advantage of the current emotion in each agent is minimal over all the others. Because there are 5 emotions in the model, the parameter *group-size* in the experiments is always a multiple of 5. All energy parameters were set to 1.0 in Experiment 1 and 2, so they would not influence the model.

To explore the effects of the parameters we defined, as output variables, *normTotalEmotion* (one for each emotion, and calculated by equation (3)), and *moodChangeProbability* (calculated by equation (4)).

$$normTotalEmotion = \frac{totalEmotion}{groupSize \times \max Emotion} \quad (3)$$

$$moodChangeProbability = \frac{totalMoodChanges}{groupSize * numTicks} \quad (4)$$

The variable *totalEmotion* corresponds to the summation among all agent of their final value of *current-<emotion>*, for each emotion. We choose to observe the totals of each emotion among all agent to have a general view of the influence of each emotion.

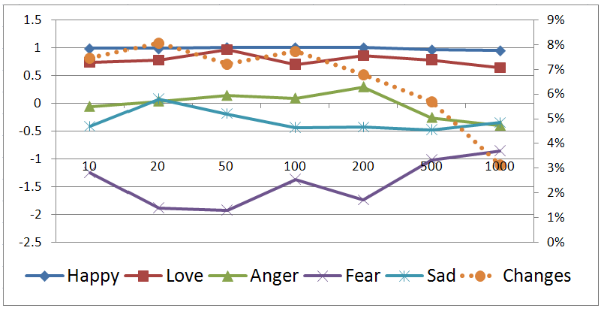

Figure 4: Experience 1 results. The x-axis indicates the value of *max-emotion*. The left y-axis indicates the value of *normTotalEmotion* and the right y-axis indicates the value of *moodChangeProbability*.

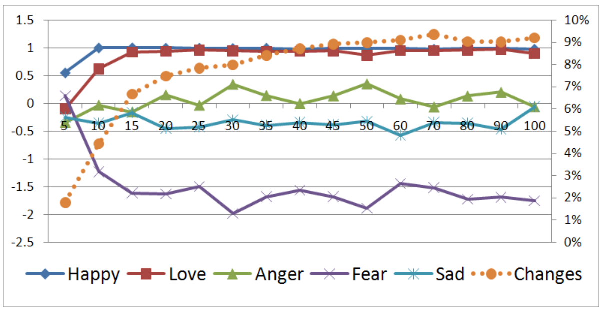

Figure 5: Experience 2 results. The x-axis indicates the value of *group-size*. The left y-axis indicates the value of *normTotalEmotion* and the right y-axis indicates the value of *moodChangeProbability*.

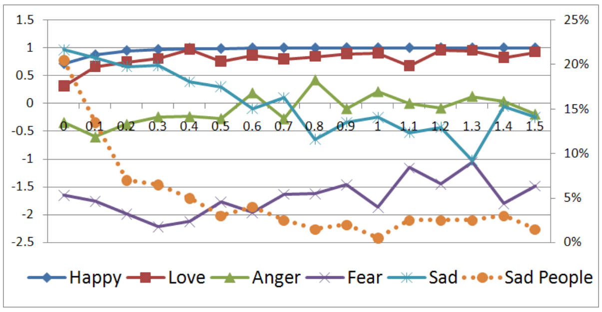

Figure 6: Experience 3 results. The x-axis indicates the value of *low-energy*. The left y-axis indicates the value of *normTotalEmotion* and the right y-axis indicates, at the end of the run, the proportion of individual whose current emotion was Sadness.

Because this value is directly proportional to the *group-size* and *max-emotion* variables, we choose to use equation (3) is used to normalize the results.

The variable *total-Mood-Changes* is the summation of the total number of times the mood changed in each agent. This variable is directly proportional to the number of agent in the simulation and for how many steps the simulation run. *moodChangeProbability* represents, in each step of the simulation, the probability of an agent to change its mood.

Each experiment was run 10 times, and we present for each value its mean.

In Experiment 1 we fixed the *group-size* at value 20, and studied the effect of *max-emotion*. In Figure 4 we have the total values for each emotion in the population at the end of the simulation. The relative positions between each emotion are fairly stable for all values of *max-emotion*, and correspond well to the relative positions for the ECS values in Table 1. There is a trend in the number of changes: the higher the value of *max-emotion* can be, the less change there is. This may happen because with a higher value of *max-emotion*, the values for each emotion saturate more slowly. In this work, an emotion changes when another emotion has the maximum value. In the experiments, there is convergence after saturation of *max-emotion*, and usually at this point, if the group is large enough, at least two emotions compete. After the values are saturated, it is more common to have changes from one of these emotions to the other.

In Experiment 2, we have fixed *max-emotion* at value 100, and studied the effect of *group-size*. For smaller groups the behavior seems unpredictable, but after a certain size, (*group-size* >= 15) it stabilizes and exhibits the same behavior as Experiment 1(Figure 5). The likelihood to change an emotion is very low in small groups. This may happen because the mood converges very rapidly and there is a higher chance for everyone to share the same mood at an early point of the simulation.

In Experiment 3, we have fixed the *group-size* at value 20 and *max-emotion* at value 100, and studied the effect of *low-energy*. As expected, the lower the probability a Sad agent will change its mood, the higher are the total values for the emotion "Sadness" (Figure 6), but this value, as well as the number of Sad agents at the end of the simulation, falls sharply when we change the *low-energy* parameter. It is noteworthy that for a *low-energy* of 0.0, where an agent which current mood is Sadness will never be influenced by others' emotions, the number of Sad agents in the beginning and at the end of the simulation is about the same (20% vs. 20.5%). This means that although the aggregate value for Sadness is the highest, which indicates other agents were affected, there was no contagion, as observed in a study by Safran [4].

5. Conclusion

In this work, we proposed a computational model for emotional contagion, based on knowledge from previous studies in this area. The Emotional Contagion Scale was used as a tool to approximate the population in the model to the real population, in relation to the susceptibility to emotion contagion. With the ECS and data from field studies, it was possible to build a population of agents that has a minimal resemblance to a real population.

The model was implemented in the NetLogo environment. In the simulation, experiments show that there was a convergence of mood that closely followed the parameters given by the ECS. In the case of Sadness, for the model to resemble what has been found in studies, it needs to make agents which show Sadness very resistant to being affected by others emotions.

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