Creation of Emotion-inducing Scenarios using BDI

Pierre-Olivier Brosseau and Claude Frasson
Département d'informatique et de recherche opérationnelle, Université de Montréal, 2920 Chemin de la Tour, Montréal, H3C 3J7, Quebec, Canada

Keywords: Inducing Emotions, BDI Agents, EEG Headset, Emotional State, Scenarios, Simulation.

Abstract: Automated analysis of human affective behavior has attracted increasing attention from researchers in psychology, computer science, linguistics, neuroscience, and related disciplines. However, existing methods to induce emotions are mostly limited to audio and visual stimulations. This study tested the induction of emotions in a virtual environment with scenarios that were designed using the Belief-Desire-Intention (BDI) model, well-known in the Agent community. The first objective of the study was to design the virtual environment and a set of scenarios happening in driving situations. These situations can generate various emotional conditions or reactions and the design was followed by a testing phase using an EEG headset able to assess the resulting emotions (frustration, boredom and excitement) of 30 participants to verify how accurate the predicted emotion could be induced. The study phase proved the reliability of the BDI model, with over 70% of our scenarios working as expected. Finally, we outline some of the possible uses of inducing emotions in a virtual environment for correcting negative emotions.

1 INTRODUCTION

The Belief-Desire-Intention (BDI) model is a well-known model in the agent community which is often used as its structure is close to the human reasoning pattern. This pattern is known as practical reasoning: using a set of beliefs we decide what we want to achieve (desire), then we decide how to do it (intentions) (Puica et al., 2013). Emotions are another component of human behaviour and, according to an increasing part of Artificial Intelligence researchers' community, they represent an essential characteristic of intelligent behaviour, particularly for taking decision. In driving situations for instance, emotions place the driver into a cerebral state that will allow or disallow him/her to react adequately to a specific situation, sometimes requiring an immediate reaction. For instance, anger and excitation can lead to sudden driving reactions, often involving collisions. Sadness or an excess of joy can lead to a loss of attention. Generally, emotions that increase the reaction time in driving situations are the most dangerous. Several questions arise. How emotions appear when a driver is exposed to a specific traffic situation? How can we measure or estimate the emotion of the driver in these situations? Can we use the BDI model to design emotional-inducing scenarios in a virtual environment? How can we train the driver to react differently and control his emotions? By creating unexpected events in a virtual environment that go against the user's desires and intentions, we have seen that we can induce controlled primary emotions. Several techniques have been used over the years to generate emotions such as emotional-inducing audio and video sequences (O'Toole et al., 2005; Pantic and Bartlett, 2007) and (Sebe et al., 2004). The American Driving (AAA) Association, estimates that the proportion of serious injuries on the road associated with aggressive behavior would be the tier two-thirds of all road accidents. In addition, for every serious accident, there are several thousands of drivers angry, if not more, who behave recklessly without reaching the point where they commit an assault. Strong emotions are the basis of this anger that gives rise to these dangerous situations on the road.

In our study we have decided to push this process further by adding human interaction in a virtual environment. The goal of our study is to design multiple scenarios in a driving virtual environment, each one with scenes able to induce a specific primary emotion.

Different technologies can be used to assess emotions. We can use physiological sensors that are able to evaluate seat position, facial recognition,

Brosseau P. and Frasson C..
Creation of Emotion-inducing Scenarios using BDI.
DOI: 10.5220/0005278505230529
In *Proceedings of the International Conference on Agents and Artificial Intelligence* (ICAART-2015), pages 523-529
ISBN: 978-989-758-074-1

voice recognition, heart rate, blood pressure, sweating and the amount of pressure applied on the computer mouse. The galvanic skin conductivity is a good indication of emotional change but its evaluation is not precise. The use of Electroencephalograms (EEG) sensors is more precise and more recently used (Chaouachi et al, 2011). In fact, EEG signals are able to detect emotions and cerebral states which, synchronized with the driving scene, can highlight what happens in the brain and when.

The organization of the paper is as follows: section 2 presents a brief review of previous works in similar fields. Section 3 presents the design of emotional scenarios based on BDI model. In section 4, we present the details of the experimental procedure. Finally, section 5 presents the results and a discussion about the impact of our findings in the field of emotionally-based environments design.

2 PREVIOUS WORK

Recently, a large body of research was directed towards improving learners' experience and interaction in learning environments. Affective and social dimensions were considered in these environments to provide learners with intelligent and adaptive interaction (Picard et al., 2001; D'Mello et al., 2009). Audio and video sequences have been used to induce emotions for a long time: (O'Toole et al., 2005; Pantic and Bartlett, 2007) and (Sebe et al., 2004) the subjects and their reactions were recorded while they were watching the emotion-inducing videos. Multiple emotions can be observed by recording the subjects' voice and faces (Schuller et al., 2007) and comparing them with audio and visual databases of human affective behavior (Zeng et al., 2009; Neiberg et al., 2006).

The different techniques used to label the emotions over the years were Self-report (Sebe et al., 2004), observers' judgment or listener's judgment (O'Toole et al., 2005) when analyzing the voice and face expressions (Pantic and Bartlett, 2007; Bartlett et al., 2005; O'Toole et al., 2005) and other biometrics means. Jones and Jonsson (Jones et al., 2005) built a system to recognize the emotion of the driver inside the car from traits analyzed in his voice. Their system combines acoustic features such as tone and volume to emotions such as boredom, sadness and anger. Research on emotions detection are currently conducted by Toyota. Their system, which is still in the prototype stage, can identify the emotional state of the driver with a camera that spots 238 points on his face. The car can then make suggestions to the driver, or simply adjust the music to relax. In our study we have decided to use the EPOC EEG headset from Emotiv to detect emotions of a driver, a system relatively easy to use and control.

From the EPOC we collect 3 main emotions: boredom, excitement and frustration. *Frustration* is an emotion that occurs in situations where a person is blocked from reaching a desired outcome. In general, whenever we reach one of our goals, we feel pleased and whenever we are prevented from reaching our goals, we may succumb to frustration and feel irritable, annoyed and angry. Typically, if the goal is important, frustration and anger or loss of confidence will increase. *Boredom* creeps up on us silently, we are lifeless, bored and have no interest in anything, due perhaps to a build-up of disappointments, or just the opposite, due to an excess of stimuli that leads to boredom, taking away our ability to be amazed or startled anymore when things happen. *Excitement* is a state of having a great enthusiasm while calm is a state of tranquillity, free from excitement or passion.

The BDI model is a model developed for programming intelligent agents. It originates from a respectable philosophical model of human practical reasoning (originally developed by Michael Bratman) (Georgeff et al., 1999); the first references of a practical implementation appeared as early as 1995 (Rao et al., 1995).

This model was developed because of its similarity with the human reasoning process (Georgeff et al., 1999). In our research, we have decided to use this model to develop scenarios in a virtual environment that will induce strong emotions of the users by going against one of their beliefs or preventing one of their intentions (Puica et al., 2013).

Following the OCC model of emotions (Orthony et al., 1988), an event can be appraised in terms of beliefs, desires and intentions, returning a certain score regarding its valence (positive or negative) and arousal (the intensity of emotion felt). In our case we will use the three emotions perceived by the EPOC to assess the impact of specific situations in driving emotional reactions.

3 CREATION OF SCENARIOS

3.1 Scenarios based on BDI Model

Scenarios

The scenarios are designed using the BDI model, associating a desire in the form of an objective that the user has to complete. The goal of the scenario is to induce a primary emotion with an intensity varying depending on the user. A complete simulation system has been developed and implemented to design and create scenarios.

Objective

The objective of the scenario is defined by a text that the participant reads before entering the simulation, it gives the participant a general idea of what he has to accomplish, and thus generating a belief and preparing the intentions that will be generated during the simulation.

Percepts

The percepts are anything that comes from the environment: stimuli or messages from the simulator, they are also influenced by the emotions of the user. (Puica et al., 2013) In our simulator the percepts are the textual objective for each scenario, the visual stimulation and the controls of the car.

Beliefs

The beliefs represent the information that the user holds when he is currently trying to complete a scenario. They are acquired from percepts. When a human is placed in a situation forcing him/her to make urgent decisions he/she will try to grasp the situation by sensing current information in the environment (Joo et al., 2013). These beliefs are also influenced by the user's emotions (Puica et al, 2013).

Desires

A desire is a goal perceived by the user when attempting a scenario. We suppose that the desire for the user is linked to what will lead him/her to a success in the scenario by fulfilling the objective. The desire to complete the objective for a scenario never changes and it is portrayed through the user's intentions throughout the scenario.

Intentions

An intention is one of the different actions that the user will chose to reach a certain desire. They are constantly revised by the user based on his current desires, beliefs, emotions (Puica et al., 2013) and the different ways to reach the goal. Users are generally committed to an intention until it is achieved or proven that it cannot be accomplished anymore. In our environment we generate events that we call **opposition events** that prevents the user from accomplishing the most obvious intentions in the scenarios.

The Expected Intention

It is the most obvious and easiest way to complete the scenario, it is this intention that we will prevent the user from accomplishing his objective.

Expected Intention = f(Beliefs, Desires)

3.2 Using BDI to Induce an Emotion

Opposition event

Our goal is to induce emotions by generating opposition and calming events in the simulation that will prevent the subject from realizing his current intention. The emotion-induction is provoked when the event occurs and prevents the user from accomplishing his intention. The user now has to find a new intention to fulfill his desire if he wants to succeed in the scenario. Opposition and calming events are at the origin of emotions generated.

Emotion Generated

The primary emotions generated comes from instinctual behavior and the secondary emotions influence the cognitive processes (Puica et al., 2013). In our study, each scenario is designed to induce one targeted primary emotion by creating an opposition to the expected intention.

Emotion Generated = g(Expected Intention, Opposition)

In the following section we will go through each scenario and describe what the Belief and Desires associated with each scenario are and the expected intention of the subject that we will use to plan the opposition event. After that, we will verify if the primary emotion induced by each scenario is the expected one. For the experiment we have defined eight scenarios.

4 EXPERIMENTATION

To collect the data we used the EPOC headset built by Emotiv. Emotiv EPOC is a high resolution, multi-channel, wireless neuroheadset. The EPOC uses a set of 14 sensors plus 2 references to tune into electric signals produced by the brain in order to detect the user's thoughts, feelings and expressions in real time. Using the Affectiv Suite we can monitor the player's emotional states in real-time.

This method was used to measure the emotions throughout the whole simulation process. The emotions are rated between 0 and 100%, where 100% is the value that represents the highest power/probability for this emotion.

The virtual environment takes the form of a game in which the player is driving a car from a bird's-eye view (Figure 1, the red car is the player's car) who is submitted to a variety of realistic situations that everybody could experience. We have developed several scenarios which can happen in current driving situations and can generate emotions. The user is submitted to a sequence of eight scenarios and emotions generated during the scenario are recorded through the EPOC system. Figure 1 shows an example of such a scenario. The user is driving his red car on the right side of the road while a Fire Truck is suddenly coming fast, activating its siren. Emotions generated are indicated on the right. Here we detect excitement, engagement, boredom, meditation and frustration.

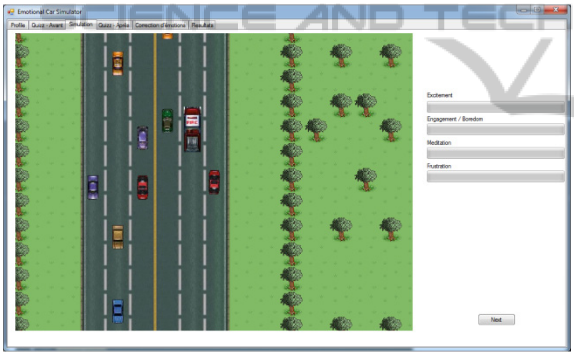

Figure 1: The Fire Truck scenario running in the Virtual Environment.

In the following scenario the user has to find a place in a public parking. There is only one place left and before the participant can reach it, another car takes it. The participant has to look around to find another place.

Figure 2: The parking place.

In another stressing scenario the user is driving normally when the brakes are suddenly no more working.

In the following scenarios we will use only excitement, frustration and boredom; we have also built and interface to plot the curves resulting from the recording of the data extracted from EPOC and showing the evolution of emotion with the time and opposition events. Figure 3 shows the increase of excitement due to a specific event which occurred

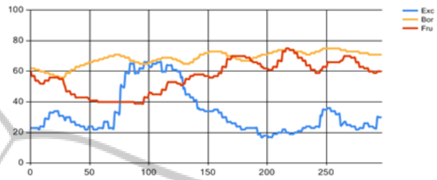

Figure 3: Evolution of emotions with time and events.

For the experiment, the user has first to register and provide personal information in the virtual environment, then he/she is submitted to a test scenario to become acquainted with the simulator. This test scenario is also used as our baseline to identify the emotions of the user using the EPOC headset. After the test scenario, the user is then submitted to the eight scenarios mentioned earlier. 30 participants were involved in the experiment. They were aged between 17 and 33, and included 6 women and 24 men. The system is coded in action script 3.0.

For each scenario the opposition event takes place at a certain time or is triggered when the user arrives at a specific place. When the opposition event is triggered, we use the Emotiv EPOC headset to register the probability of the three emotions that the user is feeling. These values are registered at a speed of 10 times per second and are saved in the database at the end of the scenario. We then proceed to analyze the results.

Correcting Agent:

To correct the negative emotions generated in the scenarios we created an agent in charge of neutralizing player's emotions (Figure 4).

Figure 4: The correcting agent.

Its soothing voice combined with its funny appearance is there to reassure the player and tell him the proper behavior to handle the scenario correctly and to reduce his emotions. In this first implementation with have created texts specific to each scenario. They contain calming advices and more explanations on the scenario in order to reduce the importance of emotion into the context.

For example the BDI components of the above scenarios are the following:

Fire Truck: Beliefs (he/she is on the highway and must go forward), Desire (to reach the end of the highway), Expected Intention (to keep going forward until he/she reaches the end).

Parking Spot: beliefs (he/she has to park the car in the parking spot), Desire (to find an empty spot and park the car), Expected Intention (to drive the car and park it in the empty spot that is visible from the start).

The corresponding opposition events and expected emotions are the following:

Fire Truck: Opposition event (after a while there is a loud siren coming from behind and the subject has to move away for the fire truck to pass), expected emotion (excitement).

Parking Spot: Opposition event (when the car arrives near an empty parking spot, another car takes the place), expected emotion (frustration).

In the BDI approach these events create a contradiction to the initial beliefs and desire and so generate negative emotions.

5 RESULTS

After the completion of the eight scenarios, we produce graphs showcasing the variations in probability and intensity of the user's emotions over time, and determine if the opposition event induced the emotion as planned. The x-axis represents the time in 10th of a second and the y-axis represents the probability that the user is feeling a certain emotion. We determine that an emotion has been induced by the event if the probability that the emotion is felt by the user has increased by at least 20% in the next 5 seconds after the opposition event. We are only looking at the variation as the base value can vary depending on the user. As we can see below (Figure 5), the probability of Excitement increases by 40% in the course of 5 seconds following the moment where Fire Truck starts its siren, therefore we can conclude that excitement has been induced by the opposition event as expected.

In the following scenario (Figure 6, parking spot) the participant arrived in a public parking. There is only one place left and before the participant can reach it, and another car takes it faster. We see the impact in terms of growing frustration. The participant has to look around to find another place and if no more place is available the frustration stays high

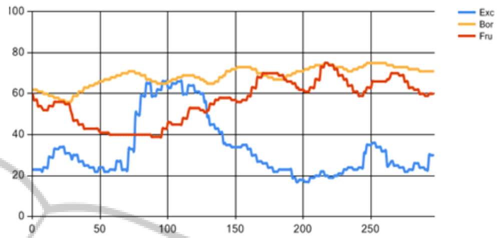

Figure 5: Raise of Excitement after the Fire Truck starts its siren.

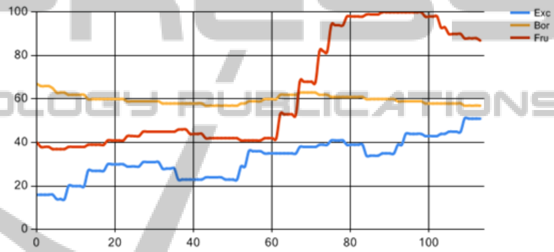

Figure 6: Raise of Frustration after the user notices that the only parking spot left was taken by a passing car.

For each scenario we have calculated the percentage of participants that have experienced each emotion and have chosen the emotion that was experienced by the highest number of participants as the observed emotion. Out of the eight scenarios, six of them resulted in having an observed emotion that matched the predicted emotion. (Table 1).

Table 1: Strongest emotion generated after the opposition event.

Scenario	Expected Emotion	Observed Emotion	Percentage of participants
Highway	Frustration	Frustration	64.7%
School Zone	Boredom	Excitement	70.6%
Intersection	Frustration	Frustration	73.3%
Pedestrian	Frustration	Frustration	52.9%
Parking Spot	Frustration	Frustration	76.5%
Brakes Failure	Excitement	Frustration	66.6%
Fire Truck	Excitement	Excitement	58.8%
Late for Work	Frustration	Frustration	64.7%

Strong emotions generated during the scenarios are corrected with the correcting agent. The efficiency is the percentage of the amount of reduction. In Figure 7 we see the impact of the correcting agent on the excitement resulting for scenario 5 (parking spot). The influence is effectively on the excitation which decreases while the other emotions are stable. We see that the decrease intervenes

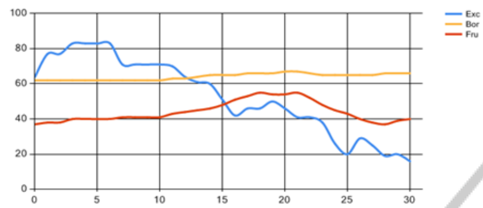

Figure 7: The effect of the correcting agent on the high excitement of the user (while the agent is talking).

The correcting agent worked with the best efficiency of 70.0% for the frustrated participants in scenario 8 (Table 2), and 66.7% of excited participants in scenario 3.

The boredom emotion is particular. It seems that when the user is in this emotion which can last for hours, he cannot evolve and change, except on special conditions that the correcting agent should deploy. This emotion can appear in educational situations when a learner for instance is no more interested by the course he is following. However, in driving situations this emotion is not really pertinent compared to excitement or frustration.

Table 2: Efficiency of the correcting agent for all the participants.

Scenario	Excitement	Boredom	Frustration
1	66.7%	21.1%	50.0%
2	50.0%	8.6%	45.5%
3	66.7%	4.8%	62.5%
4	42.9%	10.3%	66.7%
5	66.7%	19.7%	57.1%
6	46.2%	7.5%	41.6%
7	57.1%	0.0%	58.3%
8	55.6%	0.0%	70.0%
9	44.4%	4.3%	36.4%

The boredom emotion is particular. It seems that when the user is in this emotion which can last for hours, he cannot evolve and change, except on special conditions that the correcting agent should deploy.

6 CONCLUSIONS

Using the Belief-Desire-Intention model we have been able to design emotion-inducing scenarios in a virtual environment that induced emotions as intended. We had established that an emotion could be considered as generated if we saw an increase of at least 20% of the intensity of the emotion within the few seconds following the event. In six out of eight scenarios the primary induced emotion was the expected one. Our study shows that applying our system that combines the BDI model and the Emotiv EPOC is a good solution to induce a specific emotion.

After generating a strong emotion for a participant, we tested whether it was possible to reduce it using our corrective emotional agent. An emotion is considered as reduced if the observed value of probability and intensity of that emotion has declined over 20%, a few seconds after the advice of our correcting agent. Again, the obtained results were positive.

Virtual environments that are designed to correct emotional behavior would benefit from creating scenarios that use our system to target dangerous emotions (frustration for a driver for instance) and repeatedly training the user to reduce the intensity of these emotions. Further research could be made by using a more realistic virtual environment to really immerse the user and comparing the intensity of induced emotions. It would be also to test several calming scenarios to detect which one would lead to the most important reduction.

The advantage of our system is that it is now very easy to generate scenarios to provoke driver's emotions and correct these same emotions. An emotional corrective agent could easily be implemented in a car to advise the driver in relation to the emotions felt. However, in this case the major limitation of the system would be to be unable to detect the exact origin of the emotion, the emotional correcting agent having no information on what would have caused the strong emotion of the driver. It would be much more difficult to give specific advice as to not to mind when and find a new parking spot when this one is taken by another driver.

ACKNOWLEDGEMENTS

We would like to thank NSERC for funding these works. Thanks also to Thi Hong Dung Tran for having helped and participated into the experiments.

REFERENCES

Bartlett, M. S., Littlewort, G., Frank, M., Lainscsek, C., Fasel, I., and J. Movellan, "Recognizing Facial Expression: Machine Learning and Application to Spontaneous Behavior," P*roc. IEEE Int'l Conf. Computer Vision and Pattern Recognition (CVPR '05)*, pp. 568-573, 2005.

Chaouachi, M., Jraidi, I., Frasson, C.: Modeling Mental Workload Using EEG Features for Intelligent Systems. User Modeling and User-Adapted Interaction, Girona, Spain, 50-61(2011).

D'Mello, S., and Graesser, A., 2009. 'Automatic Detection of Learner's Affect From Gross Body Language', Applied Artificial Intelligence, 23, (2), pp. 123-150.

Georgeff, M., Pell, B. Pollack, M., Tambe, M., Woolridge, M. The Belief-Desire-Intention Model of Agency, 1999.

Jaekoo J., Perception and BDI Reasoning Based Agent Model for Human Behavior Simulation in Complex System, Human-Computer Interaction, Part V, HCII 2013, LNCS 8008, pp.62-71. 2013.

Jones, C., Jonsson, I. M.: Automatic recognition of affective cues in the speech of car drivers to allow appropriate responses. In: *Proc. OZCHI* (2005).

Neiberg, D., Elenius, K. and Laskowski, K. "Emotion Recognition in Spontaneous Speech Using GMM," *Proc. Int'l Conf. Spoken Language Processing (ICSLP '06)*, pp. 809-812, 2006.

Ortony, A., Clore, G., and Collins, A. (1988). The cognitive structure of emotions. *Cambridge University Press*.

O'Toole, A.J. et al., "A Video Database of Moving Faces and People," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 27, no. 5, pp. 812-816, May 2005.

Pantic, M., and Bartlett, M. S., "Machine Analysis of Facial Expressions," Face Recognition, K. Delac and M. Grgic, eds., pp. 377-416, I-Tech Education and Publishing, 2007.

Picard, R. W., Vyzas, E., and Healey, J., 2001. 'Toward machine emotional intelligence: analysis of affective physiological state', Pattern Analysis and Machine Intelligence, *IEEE Transactions on*, 23, (10), pp. 1175-1191.

Puica, M-A, Florea, A-M. Emotional Belief-Desire-Intention Agent Model: Previous Work and Proposed Architecture, *(IJARAI) International Journal of Advanced Research in Artificial Intelligence*, Vol. 2, No. 2, 2013.

Rao, A. S., Georgeff, P, BDI Agents: From Theory to Practice, *Proceedings of the First International Conference on Multiagent Systems*, AAAI, 1995.

Rao, A. S., Georgeff, P., BDI Agents: From Theory to Practice, *Proceedings of the First International Conference on Multiagent Systems*, AAAI, 1995.

Schuller, B., Muller, R., B., Hornler, A., Hothker, H. Konosu, and Rigoll, G. "Audiovisual Recognition of Spontaneous Interest within Conversations," *Proc. Ninth ACM Int'l Conf. Multimodal Interfaces (ICMI '07)*, pp. 30-37, 2007.

Sebe, N., Lew, M. S., Cohen, I., Sun, Y., Gevers, T., and Huang, T.S. "Authentic Facial Expression Analysis," *Proc. IEEE Int'l Conf. Automatic Face and Gesture Recognition (AFGR)*, 2004.

O'Toole, A. J. et al., "A Video Database of Moving Faces and People," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 27, no. 5, pp. 812-816, May 2005.

Zeng, Z., Pantic, M., Glenn I. R., and Huang, T. S. A survey of Affect Recognition Methods: Audio, Visual, and Spontaneous Expressions, Member, IEEE Computer Society, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 31, no.1, January 2009, pp. 39-57.