Emotion Selection in a Multi-Personality Conversational Agent

Jean-Claude Heudin
DeVinci Research Center, Pôle Universitaire Léonard de Vinci, 92916 Paris – La Défense, France

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Abstract: Conversational agents and personal assistants represent an historical and important application field in artificial intelligence. This paper presents a novel approach to the problem of humanizing artificial characters by designing believable and unforgettable characters who exhibit various salient emotions in conversations. The proposed model is based on a multi-personality architecture where each agent implements a facet of its identity, each one with its own pattern of perceiving and interacting with the user. In this paper we focus on the emotion selection principle that chooses, from all the candidate responses, the one with the most appropriate emotional state. The experiment shows that a conversational multi-personality character with emotion selection performs better in terms of user engagement than a neutral mono-personality one.

1 INTRODUCTION

In recent years, there has been a growing interest in conversational agents. In a relative short period of time, several companies have proposed their own virtual assistants: Apple's Siri based on the CALO project (Myers *et al.*, 2007), Microsoft Cortana (Heck, 2014), Google Now (Guha *et al.*, 2015) and Facebook M (Marcus, 2015), etc. These virtual assistants focus primarily on conversational interface, personal context awareness, and service delegation. They follow a long history of research and the development of numerous intelligent conversational agents, the first one being Eliza (Weizenbaum, 1966).

Beyond the challenge of interpreting a user's request in order to provide a relevant response, a key objective is to enhance man-machine interactions by humanizing artificial characters. Often described as a distinguishing feature of humanity, the ability to understand and express emotions is a major cognitive behavior in social interactions (Salovey and Meyer, 1990). However, all the previously cited personal assistants are based on a character design with no emotional behavior or at most a neutral one.

At the same time, there have been numerous studies about emotions (Ekman, 1999) and their potential applications for artificial characters (Bates, 1994). For example, Dylaba *et al.* have worked on combining humor and emotion in human-agent conversation using a multi-agent system for joke generation (Dybala *et al.*, 2010). In parallel with the goal of developing personal assistants, there is also a strong research trend in robotics for designing emotional robots. Some of these studies showed that a robot with emotional behavior performs better than a robot without emotional behavior for tasks involving interactions with humans (Leite *et al.*, 2008).

In this paper we address the long-term goal of designing believable and "unforgettable" artificial characters with complex and remarkable emotion behavior. In this framework, we follow the initial works done for multi-cultural characters (Hayes-Roth *et al.*, 2002) and more recently for multi-personality characters (Heudin, 2011). This approach takes advantage of psychological studies of human interactions with computerized systems (Reeves and Nass, 1996) and the know-how of screenwriters and novelists since believable characters are the essence of successful fiction writing (Seger, 1990).

Our original model is based on multi-agent architecture where each agent implements a facet of its emotional personality. The idea is that the character's identity is an emerging property of several personality traits, each with its own pattern of perceiving and interacting with the user. Then, the problem is to "reconnect" personalities of the disparate alters into a single and coherent identity.

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This can be done by selecting amongst the candidate responses the one with the most appropriate emotional state.

Our hypothesis is that such a behavior is "complex" in the meaning defined initially by Wolfram for cellular automata (Wolfram, 1984). This study propose four classes of systems: Class I and Class II are characterized respectively by fixed and cyclic dynamical behaviors; Class III is associated with chaotic behaviors; Class IV is associated with complex dynamical behaviors. It has been shown that, when mapping these different classes, complex adaptive systems are located in the vicinity of a phase transition between order and chaos (Langton, 1990). In the context of our study, Class I and Class II correspond to fixed or cyclic emotional behavior resulting in "machine-like" interactions. Class III systems are characterized by incoherent emotional responses, which are a symptom of mental illness such as dissociative identity disorder. Class IV systems are at the edge between order and chaos, giving coherent answers while preserving diversity and rich emotional responses.

In this paper we will focus on a first experiment of emotion selection in a multi-personnality conversational agent based on this hypothesis. More pragmatically, we aim to answer the following research question:

Does a conversational agent based on a multi-personality character with emotion selection perform better than a neutral mono-personality in terms of user engagement?

This paper is organized as follows. In Section 2, we describe the basic architecture for a multi-personality character with emotion selection, and Section 3 describes more precisely the emotion metabolism. Section 4 focuses on the emotion selection, which is the central point of this paper. Section 5 describes the experimental protocol and Section 6 discusses our first qualitative results. We conclude in Section 7 and present the future steps of this research.

2 EMOTIONAL MULTI-PERSONALITY CHARACTERS

The basic architecture for a multi-personality character is a multi-agent system where each personality trait is implemented as an agent.

The first agent receives the input from the user, and applies various preprocessing phases including an English stemmer, corrector, and tokenizer. It also executes a global category extraction using a general-purpose ontology.

Then the preprocessed sentence and the extracted categories are diffused to all personality agents. Thus, all these personality agents are able to react to the user's input by computing an appropriate answer message given their own state.

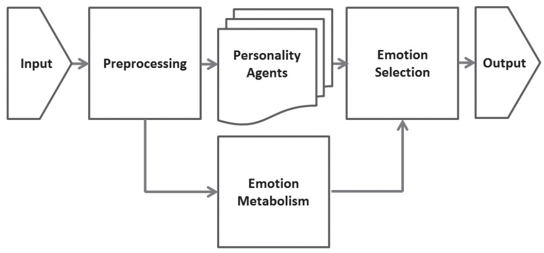

Figure 1: The architecture of the multi-personality character with emotion selection.

In this architecture the input is also linked to an emotion metabolism that computes the current emotional state of the artificial character. Then, the emotion selection agent uses this emotional state for choosing one of the candidate responses.

In the next sections, we describe the emotion metabolism and more precisely the emotion selection, since the other parts – preprocessing and personality agents – are not the focus of this paper and can be implemented using many various approaches and techniques.

3 EMOTION METABOLISM

Previously, (Gebhard, 2005) and (Heudin, 2015) have proposed models of artificial affects based on three interacting forms:

- **Personality** reflects long-term affect. It shows individual differences in mental characteristics (McCrae and John, 1992).
- **Mood** reflects a medium-term affect, which is generally not related with a concrete event, action or object. Moods are longer lasting stable affective states, which have a great influence on human's cognitive functions (Morris and Schnurr, 1989).
- **Emotion** reflects a short-term affect, usually bound to a specific event, action or object,

which is the cause of this emotion. After its elicitation emotions usually decay and disappear from the individual's focus (Campos *et al.*, 1994).

After (Heudin, 2015) we implemented this approach as a bio-inspired emotion metabolism using a connectionist architecture. Figure 2 shows a schematic representation of its principle.

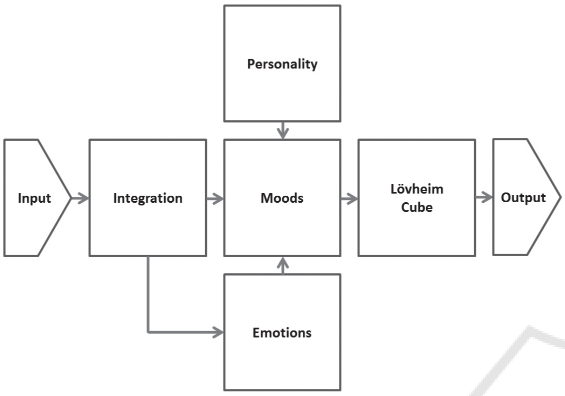

Figure 2: The architecture of the emotional metabolism.

The integration module converts the inputs to virtual neurotransmitters values. These values are then used by the three levels of affects in order to produce the output of the emotional metabolism.

3.1 Personality

This module is based on the "Big Five" model of personality (McCrae and John, 1992). It contains five main variables with values varying from 0.0 (minimum intensity) to 1.0 (maximum intensity). These values specify the general affective behavior by the five following traits:

Openness
Openness (*Op*) is a general appreciation for art, emotion, adventure, unusual ideas, imagination, curiosity, and variety of experience. This trait distinguishes imaginative people from down-to-earth, conventional people.

Conscientiousness
Conscientiousness (*Co*) is a tendency to show self-discipline, act dutifully, and aim for achievement. This trait shows a preference for planned rather than spontaneous behavior.

Extraversion
Extraversion (*Ex*) is characterized by positive emotions and the tendency to seek out stimulation and the company of others. This trait is marked by pronounced engagement with the external world.

Agreeableness
Agreeableness (*Ag*) is a tendency to be compassionate and cooperative rather than suspicious and antagonistic towards others. This trait reflects individual differences in concern with for social harmony.

Neuroticism
Neuroticism (*Ne*) is a tendency to experience negative emotions, such as anger, anxiety, or depression. Those who score high in neuroticism are emotionally reactive and vulnerable to stress.

3.2 Moods

Previous works such as (Heudin, 2004) and (Gebhard, 2005) used the Pleasure-Arousal-Dominance approach [Mehrabian, 1996]. We use here another candidate model aimed at explaining the relationship between three important monoamine neurotransmitters involved in the Limbic system and the emotions (Lövheim, 2012). It defines three vitual neurotranmitters which levels range from 0.0 to 1.0:

Serotonin
Serotonin (*Sx*) is associated with memory and learning. An imbalance in serotonin levels results in anger, anxiety, depression and panic. It is an inhibitory neurotransmitter that increases positive vs. negative feelings.

Dopamine
Dopamine (*Dy*) is related to experiences of pleasure and the reward-learning process. It is a special neurotransmitter because it is considered to be both excitatory and inhibitory.

Noradrenaline
Noradrenaline (*Nz*) helps moderate the mood by controlling stress and anxiety. It is an excitatory neurotransmitter that is responsible for stimulatory processes, increasing active vs. passive feelings.

3.3 Emotions

This module implements emotion as very short-term affects, typically less than ten seconds, with relatively high intensities. They are triggered by inducing events suddenly increasing one or more neurotransmitters. After a short time, these neurotransmitter values decrease due to a natural decay function.

3.4 Lövheim Cube

This module implements the Lövheim Cube of emotions (Lövheim, 2012), where the three monoamine neurotransmitters form the axes of a three-dimensional coordinate system, and the eight basic emotions, labeled according to the Affect Theory (Tomkins, 1991) are placed in the eight corners.

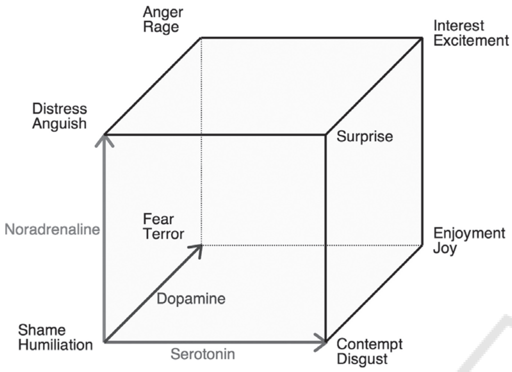

Figure 3: The Lövheim Cube of emotions.

4 EMOTION SELECTION

The emotional selection is implemented as an agent that selects one of the possible answers proposed by the set of personality agents. This section describes this selection principle in a rigorous mathematical and algorithmic way so as to make similar experiments reproducible.

In order to have a selection that follows our "edge of chaos" hypothesis, we choose a principle that is close to the fitness proportionate selection of genetic algorithms, also called roulette wheel selection (Baker, 1987). Instead of a fitness value, we use a weight proportionate to the Euclidian distance between the current character's emotional state and the one of the given personality agent in the Lövheim Cube. In other words more the current emotional state is close to that of an agent, greater is its weight.

Given:

- a set of strings representing the outputs of the personality agents: $I_0 \ldots I_n$,
- a set of weights associated to each of these possible answers: $w_0 \ldots w_n$,
- a transition function $S(t)$ returning the selected string O among the possible answers.

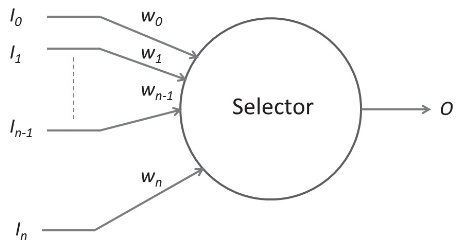

Figure 4: The emotional selector represented as an artificial neuron with a dedicated transition function.

Let the function $d(x, y)$ that calculates the Euclidean distance between two points, x and y:

$$d(x,y) = \|x-y\| = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}.$$

where $n = 3$ for a three-dimensional space. Thus, the maximum distance in the Lövheim Cube is:

$$d_{max} = d((0,0,0),(1,1,1)) = \sqrt{3}$$

The weight associated to an input I_i is then:

$$w_i = 1 - \frac{d(P_i, P_m)}{d_{max}} \quad (1)$$

Where P_i is the 3D vector in the Lövheim Cube of the agent i and P_m is the 3D vector corresponding to the current emotional state. The transition function $S(t)$ is then implemented using the following algorithm:

Algorithm: Emotional Selector.

```
Initialize w0, ..., wn-1 using Eq. 1 ;
do {
    S = 0 ;
    for ( i = 0 ; i < n ; i = i +1 ) {
        if ( Ii != "" ) S = S + wi ;
    }
    R = S * rand (0, 1) ;
    for ( i = 0 ; i < n ; i = i + 1 ) {
        if ( Ii != "" ) R = R – wi ;
        if ( R <= 0 ) break;
    }
    if ( R > 0 ) i = n – 1 ;
}
while (Ii == "" ) ;
return Ii ;
```

Algorithm 1: The algorithm used by the selector, where the function rand (0, 1) returns a random real number between 0 and 1.

5 EXPERIMENTAL RESULTS

This section describes first the prototype used in the experiment and its implementation. Then it describes the experiment protocol and results.

5.1 Implementation

We designed our own connectionist framework called ANNA (Algorithmic Neural Network Architecture). Its development was driven by our wish to build an open javascript-based architecture that enables the design of any types of feed-forward, recurrent, or heterogeneous sets of networks.

More precisely an application can include an arbitrary number of interconnected networks, each of them having its own interconnection pattern between an arbitrary number of layers. Each layer is composed of a set of simple and often uniform neurons units. However, each neuron can be also programmed directly as a dedicated cell.

Classically all neurons have a set of weighted inputs, a single output, and a transition function that computes the output given the inputs. The weights are adjusted using a machine learning algorithm, or programmed, or dynamically tuned by another network.

In the case of our experiment, the emotion selection was implemented as a single neuron with a dedicated transition function and dynamical weights as described in section 4.

5.2 The Experimental Prototype

We have implemented all modules of the architecture described in section 2 including the emotion metabolism and emotion selection.

In this prototype, we choose to develop a set of 12 very different personality traits. This decision was driven by the idea to test if our emotional selection approach promotes the emergence of a great and coherent character despite the use of these different personality traits. The 12 agents are the following ones:

Insulting
This agent has an insecure and upset personality that often reacts by teasing and insulting depending on the user's input.

Alone
This agent reacts when the user does not answer or waits for too much time in the discussion process.

Machina
This agent reacts as a virtual creature that knows its condition of being artificial.

House
This agent implements Dr. House's famous way of sarcastic speaking using an adaptation of the TV Series screenplay and dialogues.

Hal
This agent reproduces the psychological traits of the HAL9000 computer in the "2001 – A space odyssey" movie by Stanley Kubrick.

Silent
This agent answers with few words or sometimes remains silent.

Eliza
This agent is an implementation of the Eliza psychiatrist program, which answers by rephrasing the user's input as a question (Weizenbaum, 1966).

Neutral
This agent implements a neutral and calm personality trait with common language answers.

Oracle
This agent never answers directly to questions. Instead it provides wise counsel or vague predictions about the future.

Funny
This agent is always happy and often tells jokes or quotes during a conversation.

Samantha
This agent has a strong agreeableness trait. It has a tendency to be compassionate, cooperative and likes talking with people.

Sexy
This agent has a main focus on sensuality and sexuality. It enjoys talking about pleasure and sex.

Table 1: The coordinates of the 12 personality traits in the Lövheim Cube.

Personality	Sx	Dy	Nz
Insulting	0.1	0.1	0.1
Alone	0.2	0.2	0.5
Machina	0.2	0.5	0.5
House	0.2	0.7	0.2
Hal	0.2	0.7	0.7
Silent	0.5	0.1	0.5
Eliza	0.5	0.3	0.5
Neutral	0.5	0.5	0.5
Oracle	0.5	0.5	0.7
Funny	0.7	0.5	0.7
Samantha	0.7	0.7	0.7
Sexy	0.9	0.9	0.9

Given these personality traits, we assigned to each of them an arbitrary fixed point in the Lövheim cube of emotions. Table 1 gives their coordinates in the three-dimensional space.

We set the emotional metabolism personality level to a fixed neutral value:

$$Op = Co = Ex = Ag = Ne = 0.5$$

This corresponds to a neutral state in the Lövheim cube:

$$Sx = Dy = Nz = 0.5$$

The Emotion metabolism is updated by propagating the inputs using a cyclic trigger called "lifepulse". In this study we set this cycle to 0.1 second. The decay rates of the metabolism for returning to this personality neutral state were 10 seconds for the emotion level and 10 minutes for the mood level.

5.3 Protocol

In this experiment, we asked 30 university students (age 18-25) to perform a simple and short conversation with two systems: the first one was Siri on an iPad Air Retina running iOS version 9.1; the second one was our ANNA-based prototype running in a Chrome browser on a "standard" Windows PC. We choose Apple's Siri as a reference of a conversational agent with an emotionally neutral behavior.

The order of conversations was randomized. There was no topic restriction, thus the conversations could be of any subject. However, we imposed a classical three-phase structure: an *opening* phase, a *core* phase, and a *closing* phase (Linell, 1998). All interactions were text-based in English. We avoided the problem of errors related to the voice recognition system of Siri by correcting the input when necessary. The students were asked to conduct the interaction continuously and to use the same interactions for both systems in order to make the comparison easier and clearer.

In addition to the conversations, the participants also filled a questionnaire after each session. This questionnaire was inspired by the one designed by Dybala for evaluating a multi-agent system for joke generation (Dybala *et al.*, 2010).

The questions were:

1. Did you get an impression that the agent was human like?
2. Did you get an impression that the agent tried to make the conversation more interesting?
3. Did you enjoy the conversation?
4. Do you think that the agent used emotions in appropriate moments?
5. Please describe your feelings towards the agent after the interaction.
6. If you were to make friends with one of these agents, which would you choose?
7. Which agent do you think was better?

Answers for the questions 1 to 4 were given using a yes/no choice. The participants could answer freely to question 5 using a single phrase. For questions 6 and 7, the participant had to choose between the two systems.

5.4 Results

Table 2 below gives a typical example of a conversation between a student and the answers of the two systems.

Table 2: An example of a conversation with the answers of Siri and our prototype.

Example
1 – User: Hi. 2 – Siri: Hello, there. 3 – Anna: It's really nice to meet you.
4 – User: Who are you? 5 – Siri: I'm Siri. But enough about me… How can I help you? 6 – Anna: My name is Anna. I gave it to myself actually.
7 – User: What is an artificial intelligence? 8 – Siri: Here is what I found: [Wikipedia Links] 9 – Anna: An Artificial Intelligence is an intelligent computer program. It is also the research field of computer science that works on machine intelligence.
10 – User: Are you some sort of stupid program like Eliza? 11 – Siri: Well… I'm still here for you. 12 – Anna: That's very rude. You are a rude person!
13 – User: You are just a dumb software. 14 – Siri: I'm just trying to help you. 15 – Anna: I love when you do both sides of the conversation. It's like white noise it's very peaceful.
16 – User: I'm sorry. 17 – Siri: It's ok. 18 – Anna: I'm sorry too, but don't insult me anymore.
19 – User: Fine. 20 – Siri: Yes it is! 21 – Anna: Alright. Sometimes I have unexpected runtime errors too.
22 – User: Bye. 23 – Siri: OK. See you soon. 24 – Anna: Well... I finally got the last word.

Table 3 presents a summary of the results concerning the questionnaire showing that the multi-personality agent was evaluated as generally better that the mono-personality neutral personal assistant.

Concerning question 5, the comments of the participants show that most users have more “fun” with the multi-personality character. They found it “interesting” but sometimes “rude”. They emphasized the role of “humor” during conversations.

Table 3: Results of the user-oriented evaluation.

Question	Siri	Anna	Difference	Ratio
(1)	21	28	+ 7	0.23
(2)	13	25	+ 12	0.40
(3)	18	24	+ 6	0.20
(4)	12	23	+ 11	0.36
(5)	-	-	-	-
(6)	11	19	+ 8	0.26
(7)	9	21	+ 12	0.40

6 ANALYSIS

The results of this first experiment confirm our hypothesis about using a multi-personality character with emotion and remarkable personality traits. This empirical evaluation shows that it globally increases the satisfaction of the user about the conversation. The artificial agent appears more human-like than a neutral character and with a higher user engagement.

Concerning the emotional selection, which represents the central point of this paper, in the majority of cases, it was able to adapt the emotional behavior according to the conversation. Despite the use of very different personalities, the character appears globally coherent.

However in some cases, the answers made by our system were not relevant. Here is one example:

User: What is an artificial intelligence?
Anna: Have you lost faith in yourself?

This problem has potentially two causes. The first one is a malfunction of the selected agent, which selects a bad answer.

The second one is a malfunction of the emotional selection, which chooses an agent not compatible with the current emotional state. This may occur in rare situations since the roulette wheel selection has a low probability of choosing low weighted agents, but there is there is still a chance that that may happen. Another problem is that the 12 available agents do not provide a complete and homogeneous coverage of the Lövheim Cube as shown in figure 4. Designing more personality traits or at least ones with a better coverage of the three-dimensional space could solve this problem.

We must note that the user does not always interpret such an example as a malfunction since it is a common human behavior to change the subject of the conversation or to make suboptimal responses.

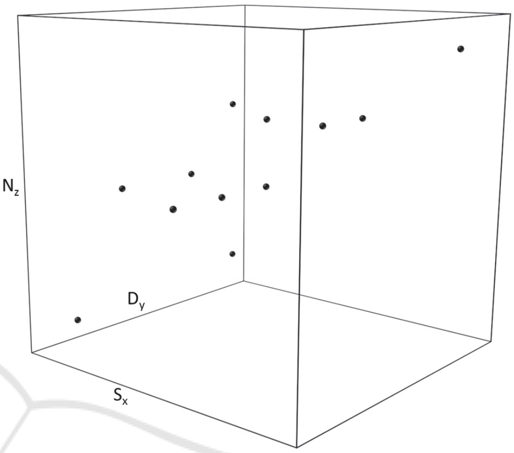

Figure 5: Repartition of the 12 agents in the Lövheim Cube of emotions showing that they don’t provide a full coverage of the three-dimensional space.

7 CONCLUSION

The experiment reported in this paper allows us to respond positively to our initial research question: *Does a conversational agent based on a multi-personality character with emotion selection perform better than a neutral mono-personality in terms of user engagement?*

Regarding the success of this first experiment, we decided to plan a larger one involving more participants. This will enable us to confirm our hypotheses with both qualitative and quantitative evaluations of user engagement. In this framework, we will conduct this new experiment online using our software platform for both mono-personality neutral character and the multi-personality character. This will also enable a blind evaluation that was not possible by using Siri as a neutral reference. In the meantime, we will develop additional personality agents in order to have a better coverage of the three-dimensional emotion space.

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