

A Multilayer Personality Model

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ABSTRACT

Virtual humans have been the focus of computer graphics research for several years now. The amalgamation of computer graphics and artificial intelligence has lead to the possibility of creating believable virtual personalities. The focus has shifted from modeling and animation towards imparting personalities to virtual humans. The aim is to create virtual humans that can interact spontaneously using a natural language, emotions and gestures. This paper discusses a system that allows the design of personality for emotional virtual human. We adopt the Five Factor Model (FFM) of personality from psychology studies. To realize the model, we use Bayesian Belief Network. We introduce a layered approach for modeling personality, moods and emotions. In order to demonstrate a virtual human with emotional personality, we integrate the system into a chat application. Thus, the system enables the developer to design and implement personalities and enables the user to interact with them.

Keywords

Virtual humans, Personality modeling, Five Factor Model, Facial animation, Bayesian Belief Network

1. INTRODUCTION

Research in virtual humans has moved ahead from sculpting and animating human figures towards imparting them autonomous behavior. At one time, an interactive communication with virtual humans was considered an almost impossible task. Today, it is attracting more and more attention by the research community. In this paper, we focus on the personality modeling or *personification* of virtual humans. Personification means attribution of personal qualities and representation of the qualities or ideas in the human form [1]. The personification of a virtual human contributes greatly to its believability. We examine the problem of personification of virtual humans from a physical, expressional, logical, and emotional point of view. It is evident from Figure 1, that each of these aspects is a complete research area in itself:

- Physical personification: This refers to the appearance of the virtual human. The facial and body features can be carefully designed to make a virtual human look like a real life person and even impart a unique appearance. The face and body model of the virtual human can be designed using any commercially available 3D modeling software or a dedicated modeling system.
- Expressional personification: The tough challenge of simulating realistic virtual human comes up while animating them. It is necessary to “design” how the virtual humans express themselves with facial expressions and gestures. Expressional personification means designing how the virtual human smiles, what is a typical way in which it expresses its anger, or even how it blinks and nods *etc.* Any parameterized facial animation system (*e.g.* MPEG-4 Facial Animation Parameters) can be used for facial expression design.
- Logical personification: This includes the way a virtual human actually analyzes input, thinks, finds answers, and chooses the natural language responses. This is probably the most tedious phenomenon to model. It requires a combination of expertise from linguistics, natural language studies, artificial intelligence, and cognitive science. This can be looked upon as the “brain” of the virtual human.

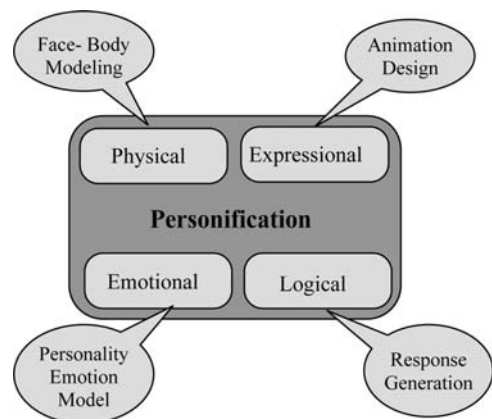


Figure 1. Aspects of Personification of Virtual Humans

- Emotional personification: The “mind” controls the way the emotions of the virtual human evolve over time and during a dialogue. We call this process emotional personification. The ability to evolve emotions makes a virtual human really different from an expert system using a knowledge database

and able to answer text queries. The emotional and logical aspects of personification are closely linked.

The main goal of this paper is to develop a system that enables the design of an emotionally personified virtual human. We focus on facial representation of the virtual human. André *et al.* [2] have given a detailed description of the work done for three projects focused on personality and emotion modeling for computer generated lifelike characters. They emphasize on the use of such characters for applications such as a virtual receptionist (or user guide), an inhabited market place and a virtual puppet theatre. They use the “Cognitive Structure of Emotions” model [3] and the Five Factor Model (FFM) of personality [4]. Ball *et al.* used Bayesian Belief network to model emotion and personality [5]. They discuss two dimensions of the personality, dominance and friendliness. El-Nasr *et al.* use a fuzzy logic model for simulating emotions in agents [6]. Velasquez proposed a model of emotions, mood and temperament that provides a flexible way of controlling the behavior of the autonomous entities [7]. There have been various other systems developed to simulate emotions for different applications. A good overview can be found in [8].

We have previously developed an autonomous virtual human dialogue system in which personality of the virtual human was modeled by transition probability matrices [9]. Emotional tags embedded in the dialogue database were used to generate facial expressions. In this paper, we present a more general multiplayer framework for modeling personality. We do not focus on a specific application, but this model could be adapted to several applications in games, entertainment and communication in virtual environments. We implement the Five Factor Model using a Bayesian Belief network. Further we propose a layered approach to personality modeling (Personality-Moods-Emotions). This approach not only makes the system implementation modular but also enables the easy and quick design of virtual humans. We enable a complete design of personality, focusing on emotional personification. Further, we explain how the emotion and personality models can be easily linked with a dialogue system resulting into a communication with an emotional autonomous virtual human.

The paper is organized as follows. We begin by describing the basic concepts used by our system. In Section 3 we explain our approach to model personality and linking it to facial animation. We give a description of the whole system and explain the individual blocks and associated concepts in details. A brief description of design parameters that can be used by a developer is given in Section 4. Finally, we conclude with future directions of research.

2. CONCEPTS

Let us clearly state what we mean by personality, emotions and moods. Personality is characteristics of a virtual human that distinguishes him from the others. Emotion is analogous to a state of mind that is only momentary. Mood is a prolonged state of mind, resulting from a cumulative effect of emotions. This section gives a brief overview of the models used to realize these concepts. The discussion is based on well-known literature in psychology, cognitive science and artificial intelligence. It is included here not only for the sake of completeness, but also to indicate how we incorporate these aspects in our system. In order to model the personality of the autonomous virtual human, we

must study the personality modeling from point of view of psychology as well as computation. There are various obvious and not so obvious aspects those are directly linked to personality. They include the choice of language, style of talking, body gestures and thinking process. In this work, we are focusing on the emotional behavior of the virtual human as a function of personality.

2.1 Personality

In psychology research, the Five Factor Model (FFM) [4][10] of personality is one of the most recent models proposed so far. The model was proposed not only for a general understanding of human behavior but also for psychologists to treat personality disorders. The five factors are considered to be the basis or dimensions of the personality space. They are detailed in the following table.

Table 1. Five Personality Dimensions

Factor	Description	Adjectives used to describe
Extraversion	Preference for and behavior in social situations	Talkative, energetic, social
Agreeableness	Interactions with others	Trusting, friendly, cooperative
Conscientiousness	Organized, persistent in achieving goals	Methodical, well organized, dutiful
Neuroticism	Tendency to experience negative thoughts	Insecure, emotionally distressed
Openness	Open minded-ness, interest in culture	Imaginative, creative, explorative

All these dimensions of personality are closely related to the expressional, logical and emotional personification to varying degrees. For example, extraversion affects the logical behavior (choice of linguistic expressions) whereas neuroticism affects the emotional behavior more closely. Nevertheless, we prefer using all the dimensions in the model, even though the focus is on emotional personality. Since, the model states that these five factors form the basis of the personality space, one should be able to represent any personality as a combination of these factors. We utilize this effectively in our implementation.

2.2 Emotions and Expressions

By emotion, we understand a particular state of mind that is reflected visually by way of facial expression. Hence, though we use emotion and expression as two different words, conceptually, we refer to the same thing by either of them. We use the emotion categories proposed by the model of Ortony, Clore and Collins [3], commonly known as the OCC model. The model categorizes various emotion types based on the positive or negative reactions to *events*, *actions*, and *objects*. The OCC model defines 22 such emotions. Table 1 shows these emotions with high-level categorization (positive and negative). The OCC model also describes how the intensities of the emotions are governed by

internal as well as external factors. We do not currently use the cognitive processing specified by the OCC model. However, the use of the emotions specified by the OCC model will facilitate the integration of a dialogue module that can generate emotions depending upon the semantics and context.

There are 6 basic facial expressions defined by Ekman [11] recognized as universal by many facial expression and emotion researchers. These basic expressions are joy, sadness, anger, surprise, fear, and disgust. They are very useful for facial animation, and can be combined to obtain other expressions. There is a partial overlap between the expressions proposed by Ekman and the ones stated by the OCC model. Only 4 expressions (joy, sadness, fear and anger) are defined in the OCC model. Surprise and disgust do not find place in the OCC model, mainly because they do not involve much cognitive processing and do not correspond to valenced reactions. However, we find them important for the expressiveness of the virtual human in a conversation system. The emotions defined by the OCC model are too many in number to directly use in the computation of emotional states. At the same time, they are important and necessary for making the dialogue rich with expressions.

Table 2. Basic Emotions

Positive Emotions	Negative Emotions
Happy-for	Resentment
Gloating	Pity
Joy	Distress
Pride	Shame
Admiration	Reproach
Love	Hate
Hope	Fear
Satisfaction	Fear-confirmed
Relief	Disappointment
Gratification	Remorse
Gratitude	Anger

We attach 24 emotions (22 defined by the OCC model with surprise and disgust as additional emotions) to the dialogue sentences in the form of tags. To reduce the computational complexity, we use only 6 basic expressions to represent the emotional states. These basic expressions are used as a layer between visible facial expressions and invisible mood, described in the later section. In order to facilitate the link between these two levels, we re-categorize the 24 emotions into 6 expression groups:

Joy	Happy-for, Gloating, Joy, Pride, Admiration, Love, Hope, Satisfaction, Relief, Gratification, Gratitude
Sadness	Resentment, Pity, Distress, Shame, Remorse
Anger	Anger, Reproach, Hate
Surprise	Surprise
Fear	Fear, Fear-confirmed
Disgust	Disgust

This modification in the emotion structure enables us to handle relatively less number of emotional states still retaining completeness necessary for expressive conversation.

2.3 Mood

In the previous subsections, we have seen the personality and emotion models. The FFM describes the personality, but it is still a high level description. We need to link the personality with displayed emotions that are visible on the virtual face. This is difficult to do unless we introduce a layer between the personality and the expressions. This layer, we observe, is nothing but mood. We clearly distinguish between mood and personality. Personality causes deliberative reactions, which in turn causes the mood to change. According to Vel'asquez [7], moods and emotions are only differentiated in terms of levels of arousal. However, we define mood as a conscious and prolonged state of mind that directly controls the emotions and hence facial expressions. Mood is also affected by momentary emotions as a cumulative effect. Thus, mood is affected from the level above it (personality) as well as the level below it (emotional state). The expressions can exist for a few seconds or even shorter, whereas mood persists for a larger time frame. The personality, on the highest level, exists and influences expressions as well as moods, on much broader time scale. This relation is shown graphically in Figure 2.

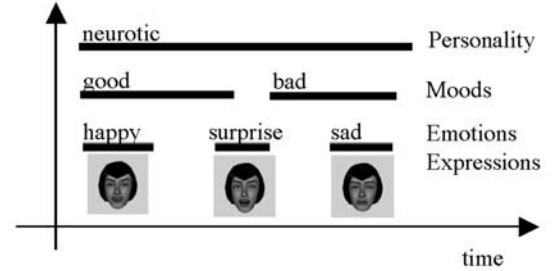


Figure 2. Layered Approach to Personality Modeling

To summarize, the following relations are made between the layers:

1. Personality practically does not change over time. It causes deliberative reaction and affects how moods change in a dialogue over time.
2. Mood, from a higher level is affected by the personality, and it is also affected from the lower level by the emotional state.
3. On the lowest level, the instantaneous emotional state, which is directly linked with the displayed expressions, is influenced by mood as well as the current dialogue state.

The emotion layer is further sub-divided into two layers as explained in the previous subsection. However, this is more of computational convenience than semantic distinction.

Considering the FFM, we observe that Agreeableness, Neuroticism, and Extraversion are the most important dimensions of the personality, as far as emotions are concerned. A neurotic person will change moods often, and tend to go into a negative

mood easily. On the other hand, an Extravert person will tend to shift to a positive mood quickly in a conversation. An Agreeable person will tend to go to positive mood more often, but frequent mood changes may not be shown.

Having emphasized the importance of mood in personality modeling, we find that it is difficult to clearly distinguish all the possible various moods. We did not find sufficient literature in psychology for analysis and classification of moods and mood changes in a systematic manner. Hence, we propose to categorize mood simply into two basic categories, namely, good and bad. So the emotions categorized by the OCC model under negative group (anger, hate, shame *etc.*) are more likely to be expressed when in bad mood. However, it may be possible that our mood forbids us from being expressive. We call this neutral mood. In this mood, the virtual human will tend not to change its displayed expression easily; also, it will tend to express itself with less intensity.

2.4 Bayesian Belief Networks

Knowing the emotional personality definitions and emotion classifications, it could be possible to write rules, mapping personality to emotional states. However, such rule-based systems are unlikely to succeed in simulating believable behaviors, mainly because uncertainty is an important aspect of human behavior. Thus, we need a computational model that can handle uncertainty while retaining the underlying principles. The Bayesian Belief Network (BBN) is the natural choice as it is used to model domains containing uncertainty [12]. Syntactically, it is a Directed Acyclic Graph, each node in this graph represents a state variable with mutually exclusive and independent states. The directed links represent influence of the parent node on the child node. For each child node, a conditional probability table defines how its states are affected for each combination of possible states of the parent node. Thus, the effects (children) of the causes (parents) are encoded probabilistically into the definition of the BBN. How to initialize the transition probability values, to clearly represent the causes to effects relationship for a particular application, is altogether a different topic of research. For our application, we set the conditional probability values by intuition.

The BBN is particularly suitable for modeling complex phenomenon such as personality because of the following reasons:

1. It handles uncertainty powerfully, which is evident in evolution of emotions.
2. It gives structured probabilistic framework to represent and calculate otherwise very complex and rather abstract concepts related to emotions, moods, and personality.

Ball *et. al.* [5] previously have reported the use of the BBN for personality and emotion modeling. The main difference in their approach and our approach is that we try to use the FFM of personality to devise a way of combining personalities and also introduce an additional layer of “mood” in the model.

3. SYSTEM OVERVIEW

In this section we present an overview of the emotional virtual human system that we have developed. Figure 3 shows the various components of the system and their interactions. For the expressional personification, we use MPEG-4 Facial Animation Parameters and the real-time facial animation system using FAPs [13].

A text processing and response generation module processes the input text; in our case it is the chat-robot ALICE [14]. ALICE uses Artificial Intelligence Mark-up Language (AIML), which is an XML based language, to define dialogue database. We define the AIML database such that the emotional tags are embedded in the responses. The emotional tags have probability values associated with them. These emotional tags are passed on to the personality model, which is a BBN. The personality model, depending upon the current mood and the input emotional tags, updates the mood. As mood is relatively stable over time, this mood switching is not a frequent task. Depending upon the output of the personality model, mood processing is done to determine the next emotional state. This processing determines the probabilities of the possible emotional states. Though the system uses emotion tags in dialogues for evolving emotions based on mood and personality, it is possible to link the model with an affective reasoner, which can provide similar tags for emotion appraisal. The personality and mood model can process emotional tags irrespective of the process that derived them. The synchronization module analyses previous facial expression displayed and output probabilities of the mood processing. It determines the expression to be rendered with appropriate time envelopes. It also generates lip movements from the visemes generated by the Text to Speech engine. It finally, applies blending functions to output the facial animation parameters depicting “expressive speech”. We use the technique described in [15] for this. A separate facial animation module renders the FAPs in synchrony with the speech sound.

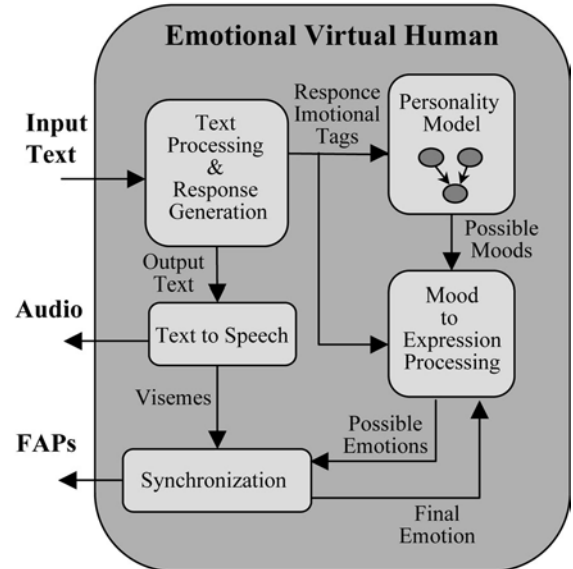


Figure 3. System Overview

3.1 Text Processing and Response Generation

In order to simulate the logical personification, we use a chat-robot ALICE. ALICE is an open source project hosted by the ALICE AI foundation. ALICE uses AIML (Artificial Intelligence Mark-up Language) to maintain a database of possible user inputs. The user input is matched with the AIML database entries and a corresponding template response is generated. The simplest AIML entry looks like the following:

```

<category>
<pattern>What is your name?</pattern>
<template>My name is ALICE, nice to meet
you!</template>
</category>

```

All the AIML categories are not such strict matches. AIML uses various tags to introduce randomness in answers, to remember limited dialogue history, and to allow symbolic reduction. Though ALICE does not use any syntactic or semantic language analysis techniques, the features embedded in AIML and ALICE make the chat robot much more than a mere pattern matching program operating on a set of possible inputs and answers. It can engage the user in believable conversation to a considerable degree. Though originally designed for merely a chat application, AIML can be generated to tackle a particular domain queries from the user, e.g. a sales assistant or a virtual receptionist. For a complete description of AIML, the interested readers are referred to [14].

We notice that current state of natural language processing does not allow us to relate dialogue with emotions easily and generally. Hence, we extend AIML to incorporate emotional tags in the responses. Each response may be associated with one or more emotional tags. These tags essentially represent possible emotional state of the virtual human while rendering the particular response. Currently, we use the 24 emotional tags as explained in Subsection 2.3. However, it is easily possible to extend this list. It could be useful to introduce *bored*, *thinking* and *frustration* as new tags belonging to sad, neutral and anger expression categories respectively. Consider a particular response “I am very busy now a days”. This response can be associated with pride or distress. Subsequently, we can associate probability values to these possible emotions. For this particular response sentence, probability of *pride* is set to 30% and that of *distress* is 70%. The corresponding AIML category looks like the following:

```

<category>
<pattern>what are you doing?</pattern>
<template><emo name="pride" prob="30"><emo
name="distress" prob="70">I am very busy now a
days.</template>
</category>

```

The introduction of emotional tags is not a trivial task. It is necessary to imagine various situations that may give rise to various emotions according to the meaning of the response sentence. A response like “I am happy to hear that.” can mostly be associated with emotional tag *joy* with 100% probability. This ensures higher probability of joy being expressed finally as a result of the emotion-processing pipeline. We subsequently explain how these tags and corresponding probabilities are processed by the personality and mood model to generate the final emotional state.

In order to facilitate introducing a variety of emotional tags with each and every possible response, we have developed an interactive tool enabling easy and quick design of “emotional” AIML. For improving the naturalness of the dialogue, we propose further modification in AIML. Instead of attaching different emotions to a single response, while creating the AIML database, we input different responses corresponding to different emotions. For example, a typical modified AIML category will look like the following:

```

<category>
<pattern>How are you?</pattern>
<template>
<emo name="joy" prob="50" res="I am fine, thank
you.">
<emo name="sadness" prob="50" res="Not so good
today!">
</template>
</category>

```

The emotional tags are processed by the personality and mood processing modules. Subsequently, the processing will result into not only appropriate emotion, but also a selection of the speech response analogous to the emotion.

In future, it is possible to replace ALICE with a more sophisticated language analysis module. Such a module should create the emotional tags depending upon the semantics, context and dialogue history of the conversation, in a more coherent way.

3.2 Personality Model using BBN

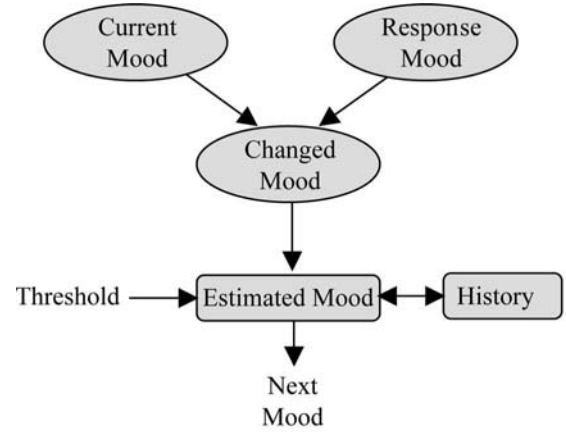


Figure 4. Personality Model

As proposed by the FFM of personality [4], the five factors form the basis of the personality space. Hence, it should be possible to “design” any personality by a linear combination of these factors. In this section we explain the use the BBN to model personality. Figure 4 shows a typical BBN we use. It is a simple structure containing two parent nodes and one child node.

We create one BBN for each basic factor of the personality. A user can specify the desired combination of these five or less factors. For example, it is possible to model a personality being 30% Neurotic and 70% Extrovert. The corresponding prior and transition probability values are combined and normalized to get the desired personality model.

The “Current Mood” (denoted by m_c) node as well as the “Response Mood” (denoted by m_r) node can take up three possible values; good, bad or neutral.

$$m_c, m_r \in [\text{good, neutral, bad}]$$

The initial value of the “Current Mood” can be decided by the personality design. The “Response Mood” is nothing but the

categorization of the emotional tags extracted from the output of the response generation module. The default “Response Mood” is set to neutral. For example, pride and distress are associated with good and bad moods respectively.

The personality model, denoted by π , has the transition probability values encoded that decide how the next mood is selected. These probability values reflect the psychological processing of emotions. Imagine a person in bad mood sees his colleague. If he is agreeable by nature, he would tend to get into good mood quickly, assuming that the conversation starts with greetings and with pleasant topics. Thus the mood of a person is affected by the state of conversation as well as his personality. With the configuration of BBN suggested here, one can easily decide how a personality affects the change in mood during the conversation. Simple Bayesian calculation with transition probabilities and the prior probabilities ($P(e_i)$) gives us the probability of mood change. This probability of mood change is calculated for each of the possible emotions embedded in the response as shown by the following pseudo-code:

```
for each emotion  $e_i$  in response
   $m_r$  = mood corresponding to  $e_i$ 
  for each possible mood  $m_n$ 
     $P(m_n) = \text{BBN}(m_c, m_r, \pi)$ 
     $= P(m_n | m_c, m_r) \cdot P(e_i)$ 
```

where $P(m_n | m_c, m_r)$ denotes the conditional probability for mood change as per the personality model π . The emotion causing higher probability $P(m_n)$ is selected as a candidate to decide the mood change. For example, for estimating the changed mood, we calculate $P(\text{good})$, $P(\text{neutral})$ and $P(\text{bad})$ for the next mood using the values $P(\text{pride}) = 0.3$ and $P(\text{distress}) = 0.7$ and the transition probability values encoded in the model. If there are more than one good or bad emotions in the response, we add the corresponding probabilities.

Further, the user can set a threshold value for the probability of mood change. If $P(m_n)$ is greater than this threshold, m_n is selected as the next mood, else previous mood is retained. Also, “History” maintains the probabilities of mood change from the previous response processing. This history influences the decision about probability of mood change by way of simple rules. For example, let us assume that previous response resulted in a mood change from good to bad with a probability less than the threshold, and hence the mood change did not take place. If the next response evoked the same mood change (good to bad), the transition now becomes more probable, even though the current probability of mood change is low.

The decision to select between the emotional tags (pride and distress in our example) is delayed till the next stage in emotion processing. However, if the next mood computed is good, the chances of good emotion (pride, here) being selected for final expression increase, though this decision will also be influenced by the current facial expression. The probability of mood change indicates how easy it has been to shift the mood, if at all. The probability values for all possible mood change (m_c and $P(m_n)$) are stored in history to be used for next computation.

3.3 Mood to Emotions

Once we choose the next mood or retain the previous mood it is necessary to actually select the emotional state, the appropriate

response and subsequently facial expression. The emotional state is decided by three factors: the response generated by AIML, the current mood (output from personality model, m_n), and the previous emotional state (denoted by e_p). Careful introduction of emotional tags in the response, during generating the AIML database, takes care of the first factor. In order to link all these three factors, we define transition probability matrices for each mood. These matrices indicate probabilities of transitions from one emotional state to another. It is obvious to set higher probability transition values for moving towards negative emotions for a bad mood. Since we use six basic expressions as a categorization of 22 emotions, our matrix has a dimension of 7X7 (6 expressions plus neutral). Here, we notice the usefulness of choosing only 6 basic expression categories as against 22 emotions defined by the OCC model. Figure 5 shows a typical transition probability matrix for good mood. The first column represents the previous expression and the first row represents the next expression. Thus, if the current expression belongs to category *joy*, then the next expression being of the category *sadness* has a probability of 0.05.

	Joy	Anger	Sadness	...	Neutral
Joy	0.8	0.1	0.05		0.05
Anger	0.6	0.2	0.1		0.1
Sadness	0.7	0.05	0.05		0.2
...					
Neutral	0.9	0.0	0.05		0.05

Figure 5. Transition Probabilities for Good Mood

Let e_r denote the emotion embedded in the response and takes any of the 24 values for emotions. $P(e_r)$ denotes the probability as encoded in the tag. The corresponding expression category (one of six basic expressions) is denoted by $Ex(e_r)$. The following pseudo-code indicates computation of next emotional state:

```
for each emotion  $e_r$  in response
   $P(e_n) = \Gamma m_n(Ex(e_p), Ex(e_r))P(e_r)$ 
```

where Γm_n represents the transition probability matrix for the mood m_n . Such probability transition matrices are defined for each mood and each personality. Currently these values are being set using intuition and general understanding of human mood. However, testing the system with various users help us fine-tune these values for obtaining increasingly believable results. Similar to the personality model, a threshold value is set to deduce the next emotion. It may be possible that two emotions show probability higher than the threshold. In this case, the synchronization module decides rendering of these multiple emotions. The emotions have short durations. Further, the synchronization module finally decides the expression to be rendered with smooth transition between different emotions. Hence, we do not maintain history of change of emotions. Separating the processing of mood from that of emotion allows us to have various possibilities like changing emotion without changing mood, changing mood without changing emotion, or changing both mood and emotion as the case may be depending upon the conversation and mood history. A series of positive emotions increases the probability of transition to a good mood

and a good mood increases the probability of selecting a positive response subsequently.

3.4 Synchronization

As stated previously, by emotion, we understand a particular state of mind that is reflected visually by way of facial expression. Thus, we map emotional state directly to the facial expressions. For improved realism, it is extremely important to synchronize speech movements and facial expressions assuring smooth blending, avoiding any possible abrupt changes. The emotion associated with an utterance has to be rendered during the speech animation for that utterance. We use attack-sustain-decay-release type of envelope for expressions and blending technique discussed in [15] for achieving this. Currently, we decide the activation time by the length of speech; however, we are doing more tests in order to increase realism. Following steps summarize the process of synchronization:

1. Analyse the output of the mood model that gives probabilities of all the emotions possible. If the highest probability is less than 10% higher than that of the second highest probability, and if both the emotions belong to the same categorization (positive or negative according to Table 2), a blend between the expressions is used. The corresponding probability values are used as normalized weights. If the emotions belong to different categories, simply the one with the highest probability is selected.
2. Compare previously activated expression with current expression. If the two belong to different categories (positive and negative), apply relaxed transition. Relaxed transition allows less steep “attack” envelope.
3. Finally, blend the expressions with the visemes to generate the FAPs corresponding to “expressive speech”. The output is sent to the facial animation rendering module.

For improved realism, we also add periodic facial movements like eye blinks and nodding. Though we are not emphasizing here the synchronization of blinking, nodding and gestures with speech, there are well-studied schemes that can be integrated in our system [16].

4. DESIGNING PERSONALITIES

So far we have explained the techniques used and described the system developed in details. From time to time, we have mentioned that the user of the system can design the various modules by defining parameter values. In this section, we briefly summarize the possibilities of the system design by a user, who may be an emotion researcher, experimental psychologist or computer graphics animator. The system mainly focuses on emotional personification. Several other tools can be used to realize physical and expressional personification.

For the emotional personification, following are the steps taken by the designer of the personality:

4.1 Personality Parameters

As described in Section 3, following parameters are necessary to specify in order to define a personality:

1. Initial value of “Current Mood”, though normally this is set to neutral.
2. Conditional probability values for each BBN corresponding to each personality factor.

3. Weights deciding the combination of the five factors of the personality model.
4. A threshold value (0 to 1) for mood change decision. If the probability of mood change is above this value, the mood change takes place.

4.2 Mood Parameters

The following list indicates the parameters related to mood that can be set by the user:

1. Initial emotion or facial expression, though normally, this is set to neutral.
2. All the three transition probability matrices for good, neutral and bad mood. The designer can design her own matrices, or select from pre-defined matrices. Further, these matrices can be different for each personality.
3. Threshold value (0 to 1) that decides whether to change the current emotional.

4.3 Synchronization Parameters

It is possible to have several parameters for the synchronization of facial expressions and speech. We have provided the following parameters:

1. Time envelope of the facial expressions: triangular, attack-sustain-decay-release, or spline. It is possible to attach these envelopes for all the emotions.
2. Time duration of attack in percentage of the total duration, in case of relaxed transition.
3. Blinking and nodding frequency default values and how they are affected by different emotions, *e.g.* blinking frequency may reduce in the emotional state of fear. However, currently this support is limited and we intend to broaden this in the course of further development.

5. DISCUSSION AND CONCLUSION



Figure 6. Expressive Speech Animation

We have prepared a dialogue scenario that best shows the strength of the model. We simulate a conversation between a manager and his virtual assistant. Since our focus is to demonstrate change in emotions governed by dialogue content as well as the personality, we have “designed” the dialogue that has many possibilities for

emotions. For each possible input, we encode various possible responses attributed to different emotional states as described in Section 3.1. From these possibilities, the personality and mood-processing module selects the final response. Indeed, designing such a general AIML is a painstaking task. With the availability of an intelligent dialogue system capable of generating various possibilities depending upon the context, the need of creation of such an AIML would be eliminated.

The accompanying video clips show the recordings for the two personalities. The movie clips can also be downloaded from

<http://www.miralab.unige.ch/~sumedha/personality/>

We have designed two contrasting personalities, agreeable and neurotic. We have chosen to model these traits, because they are clearly distinguishable mainly from emotional behavior and facial expressions. In the beginning of the conversation, the moods of both the personalities are set to neutral. The inputs appear on the screen as typed text. The mood change is also seen on the left corner of the frame. The agreeable personality tends to be pleasant. The neurotic personality, on the other hand, tends to change to a bad mood more easily. However note that, a good mood does not mean always a smiling face, as explained at the end of Section 3.3. Since both the mood and emotion computations are probabilistic, the final expressions may not be exactly the same, each time we run the dialogue. However, the overall trend of the mood changes is similar. Figure 6 shows the snapshots from the animation depicting various facial expressions during the conversation.

Apart from the lack of an intelligent dialogue system, we are aware of several aspects for further improvement. Integration of real time speech recognizer will considerably add to the usability. Further, controlling voice intonation and talking speed according to emotions would bring out the real expressiveness of the character. Development of such modules or integration of such already available modules remains an important future task for the completion of the system. Within these limitations, the effectiveness of the multilayer personality model is evident.

It is a challenging but interesting task to fine-tune the conditional probabilities of the personality Bayesian Belief Networks and mood transition probability matrices. We continue to learn by experiments. We have identified the need for thorough experimentation by users and researchers from various backgrounds. The system has a great potential to be used by the emotion researchers and psychologists to study and validate the model and make improvements.

To conclude, we have developed a system incorporating a personality model for an emotional autonomous virtual human that covers the following important aspects:

- Many concepts are brought together from psychology, artificial intelligence and cognitive science to create a layered model of human personality directly affecting the emotional and expressional behavior.
- A user is able to design personalities for virtual humans as a combination of five basic factors. Furthermore, the user can define moods for a virtual human and how these moods affect the emotional state and displayed expressions.
- The model has been integrated with a chat system, demonstrating the potential use of such a model in a real life

system enabling believable communication with a virtual human in a natural language.

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