

Text Mining for Fuzzy-based Emotion Expressions

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Abstract—A model of emotion representation in the form of facial expressions using text mining technique, followed by fuzzy-based mechanisms using Fuzzy Inference System (FIS) is proposed. The model classifies the emotional content of sentences from text input and expresses corresponding emotions by a facial expression. Text input is classified using Naïve Bayes text classifier, while facial expression of a virtual character are controlled by Mamdani fuzzy inference system utilizing results from text classifier. This model is able to show the facial expression with admixture blending emotions. As a demonstration, examples of facial expressions with corresponding text inputs as results from the implementation of our model are shown.

Keywords—text mining, emotion detection in text, Naïve Bayes Method, Fuzzy Inference System, facial expression, virtual character

I. INTRODUCTION

The interest in computational models of emotion and emotional expressions has been steadily growing in the intelligent agent research community. Several psychologists have acknowledged the role of emotions in intelligence [1]. Minsky stated that, "the question is not whether intelligent machines can have any emotions, but whether machines can be intelligent without any emotions" [2]. There is already a trend towards designing Human Computer Interaction (HCI) system which utilizes social interfaces, mimicking human-to-human communication properties. In this paper, the computer is a social actor, that is a social embodied agent. The general vision here is that if a machine could recognize a user's emotion, the interaction between man and machine would become more natural and efficient. The machine, i.e. computer, could offer help or assistance to a confused user, try to cheer up a frustrated user, or simply empathize with the user's situation.

Life-like virtual character convincingly implements the "computer as social actor" metaphors as its modalities include affective speech, facial emotional expressions, hand gestures, head movements and body posture. It is designed to establish socioemotional relationships with human user. Since life-like virtual character is endowed with some tools to express emotions, it is genuinely able to display (artificial) empathy to the human user. We believe that life-like virtual character technology may significantly improve human computer interaction.

Embodied conversational agent which performs tasks through conversational, natural language-style dialogs with user contrast the traditional view of computers as enabling tool for functional purposes. It is believed that such interfaces have great potential to be beneficial in HCI for a number of reasons. Agent could function as a smart virtual assistant, much like travel agent or investment advisor [3].

An embodied agent could show gaze patterns, facial expressions, and gestures, in addition to words and sentences, for conveying information and affect [4].

Affective computing extends HCI by including emotional content together with appropriate means of handling affective information [5]. The first step of this application is Human Emotion Recognition (HER). In HER, the data collected to recognize human emotion is often similar to the signals that human use to perceive emotions of others. Hence, HER is naturally multimodal. It includes textual, visual (graphical) and acoustic (sound) features. The study of text-based emotion mostly done due to text form is relatively simple compared to other forms such as graphical or sound. HER from text can be considered as a classification task of a given text according to predefined emotional classes. A number of classification methods have been proposed to make the process of recognition of text-based human emotions, such as SVM (Support Vector Machine), VSM (Vector Space Model) and Naïve Bayes [6, 7].

In this paper, once the emotions carried by text-based sentence have been classified, the embodied conversational agent (life-like virtual character) will respond appropriately using facial expressions through its face model. Facial expressions are controlled by mechanism which based on Fuzzy Inference System (FIS).

Application of this research can be found in the next generation of intelligent robotics, virtual human, NPC (Non Player Character) in game, embodied conversational agent itself, psychology, blogs, product reviews, and to support development of emotion-ware applications such as emotion-ware Text-to-Speech (TTS) engines for emotional reading of text.

II. DESIGN OF THE SYSTEM

Proposed system as depicted in Fig. 1 is organized into two parts, namely (i) emotional classification based on text-mining technique using Naïve Bayes classifier and (ii) fuzzy-based facial expression of face model controlled by FIS.

Automatic text classification have been used in many applications such as e-mail filtering, topic identifications, automatic meta-data organization, text filtering and documents' organization for data-bases and web pages [8, 9, 10].

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The dominant approach to automatic text classification is based on machine learning techniques: a general inductive process automatically builds a classifier by learning, from a set of preclassified documents, the characteristics of the categories. The advantages of machine learning approach over the knowledge engineering approach (consisting in the manual definition of a classifier by domain experts) are a very good effectiveness, considerable savings in terms of expert manpower, and straightforward portability to different domains [11].

Many techniques for supervised learning algorithms for text classification have showed reasonable performance. These techniques include Naïve Bayes, k-nearest neighbor, SVM, boosting and rule learning algorithms. Among these, however, no single technique has proven to consistently outperform the others across many domains [12, 13, 14, 15, 16, 17, 18].

In our experiments, Naïve Bayes (NB) text classifier is used because it is fast, easy to implement and despite of its simplified assumption on independence, in practice NB often competes well with more sophisticated classifiers [19].

NB classifier utilizes libbow [20]. Given a text input T , libbow estimates the probabilities based on training set, then selects the class with the highest probability as assigned emotion class C of given text T . That is to say, text T is assigned to emotion class C_i if and only if $P(C_i|T) > P(C_j|T)$ for all j such that $1 \leq j \leq n$, $i \neq j$, where n is number of emotion class. As depicted in Fig. 2, Naïve Bayes model can be viewed as Bayesian network in which each class C_i has T as the sole parent and T has no parents [21].

where

$$\sum_{i=1}^n P(C_i|T) = 1$$

Probability, for a Bayesian, is a way to represent a degree of belief in an event, given the evidence. An impossible event has a probability of 0, and a certain event has a probability of 1. It means that text T is categorized to single emotion class C_i with the highest degree of belief and a number of lower degree of beliefs to the other classes of emotion C . In term of basic emotion classification from text, we postulate, a sentence T will generate the one "strongest" (highest probability value) basic emotion and a number of "weaker" (lower probability values) basic emotions. In the other words, we imply, a sentence T will generate the one strongest emotion and a number of weaker emotions.

Unlike the usual usage of text classification which is to classify a text T to one class C of emotion by using only the highest value of probability, in our system, all of probability values from NB classifier are employed. Therefore, a facial expression will be triggered from a mixture of emotions. Dataset used in our experiments came from ISEAR (International Survey on Emotion Antecedents and Reactions) which was conducted in 1990s across 37 countries and had almost about 3,000 respondents. ISEAR dataset consists of 7,666 sentences and snippets in English, categorized into 7 (seven) classes of emotion: joy, fear,

anger, sadness, disgust, shame, and guilt [22]. This dataset contains text documents of about 3-4 sentences preclassified into the categories of emotion. Table 1 shows some sentences taken from ISEAR dataset with their corresponding emotions. Due to reason that guilt can not be expressed by a simple facial picture (which explained in later section), guilt is excluded from our experiments.

Psychologists have tried to explain the human emotions for decades. However, they have not yet agreed upon a set of basic human emotions, as shown in Table 2. They disagree on the exact number of affects, i.e. basic emotions, but most include 5 (five) namely joy, sadness, anger, fear, and disgust [24, 25].

A well-known model of emotions is the work of [26]. He uses basic emotions as building blocks for derived emotions; secondary emotions and even ternary emotions. All other emotions are mixed or derivative states. They occur as combinations, mixtures, or compounds of the basic emotions, as depicted in Fig. 4 believed there exists a relationship between facial expression and emotional state [27].

The proponents of the basic emotions view, assume that there is a small set of basic emotions that can be expressed distinctively from one another by facial expressions [28, 29, 30]. For instance, when people are angry they frown and when they are happy they smile.

The six basic emotions can be associated with a set of facial expressions [28]. Designed a face model with 6 (six) facial expressions of basic emotions depicted in Fig. 3 which are sadness, joy, anger, fear, disgust, and surprise [23]. Table 3 shows textual descriptions of facial expressions as representations of basic emotions, taken from [31]. In our experiments in this paper, surprise is excluded due to unavailability of surprise class in the training set from ISEAR dataset, however facial expression of shame is added, based on psychological researches.

Although guilt, shame and embarrassment are terms meant to refer to different emotions, researchers attempting to demonstrate distinctions in how people actually experience these emotions are likely to encounter challenging difficulties [32]. Specifically, even though these emotions are distinct [33], guilt does not have a distinct facial display [34, 35]. Guilt may involve a complex pattern of facial, gaze, postural, and speech activity [36] that can not be displayed merely by a static facial picture. Therefore, guilt is excluded from our experiments.

Further question to be answered is "Does shame have distinct facial expression?" The English word "red-faced" has a Chinese equivalent *lianhong* (literally "face-red"). Both suggest a connection between shame and facial display [32]. A number of non verbal behaviour could indicate shame. They include hiding behaviour such as covering all or parts of the face, gaze aversion, with eyes downcast or averted, bowed head, hunching shoulders, squirming, fidgeting, blushing ("red-faced"), biting or licking the lips, biting the tongue, or false smiling [34, 37]. Eyes downcast and unique mouth shape (as result from lips biting) are chosen to represent shame facial expression in our experiments.

Another aspect to consider is the intensity of emotion. In everyday life, emotions often occur in mixtures. For example, the feeling of sadness is often mixed with shame, anger or fear. People typically respond to social events with an admixture of emotions, with varying degrees of intensity. Plutchik's model like many others also explains the notion of emotion intensity, that represents the strength by which an emotion is felt.

Our goal is to build a system which able to generate facial expression of face model by a mixture of emotions, with each emotion may have its own different intensity.

This model has a major advantage, because it significantly decreases the complexity of classification due to a small number of basic emotions to which the system can be restricted. For modelling of different degrees of membership to different classes in a classification task, namely emotion expression, fuzzy-based method is a very useful approach.

In our proposed system, the intensity of basic emotion through FIS controls the Facial Animation Parameters (FAP) of face model. Borrowing MPEG-4 terminology, the FAP value for a particular FAP indicates the intensity of the corresponding action, for example a big smile (stronger joy) versus a small smile (weaker joy). Table 3 shows textual description of facial expressions with their corresponding emotions, taken from [31]. A neutral state of face or a face without emotional expression, is also needed to be added.

Ludwig as face model is utilized for our experiments. Ludwig is a full body fully rigged and animation ready character for Blender [38]. Blender is a free and open-source 3D graphics application that can be used for 3D modelling and rendering.

Ludwig has the following face controls: eyes including eyebrow, eyes direction, mouth including jaw, lips and tongue, also capability to sneer. In our experiments, following controls are used:

EyesDirection, BrowPosition.R/L, -
BrowEmotion.R/L, BrowWrinkle, EyeOpen, Sneer.R/L
and MouthSmile.R/L.

Parameter setting is done by visual observations of Ludwig face for lowest and highest value for face control as ranges of operating parameter values (see Table 4). Table 3 is referred as guidelines to manually set facial parameters to display facial expressions for 5 (five) basic emotions, while as an addition, shame is facially expressed by eyes downward and lip biting as revealed by our investigation in previous section. Fig. 5 depict facial expressions of Ludwig in neutral, basic emotions, and their corresponding face control parameters.

In our proposed system, fuzzy inference is the process of formulating the mapping from a given input; that is, probability values as results from NB classifier, to an output; that is, face controls using fuzzy-based mechanism.

The process of fuzzy inference involves Membership Functions (MF), logical operations, if-then rules, aggregation and defuzzification to produce output. In previous experiments conducted by [39, 40] using FIS implemented in Matlab, the number of rules were too

many, not carefully evaluated. There were total 120 rules, covering 6 (six) face controls, EyesDirection not included.

In this paper, rules are simplified. Total rules are 49, covering 7 (seven) face controls, consist of EyesDirection 2 rules, BrowPosition 5 rules, BrowEmotion 5 rules, BrowWrinkle 7 rules, EyeOpen 9 rules, Sneer 5 rules, MouthOpen 7 rules and MouthSmile 9 rules.

Furthermore, instead using Matlab FIS, in this paper, FIS Mamdani is implemented using java-based jFuzzyLogic software which supports FCL (Fuzzy Control Language) [41] file format. FCL is a standard for Fuzzy Control Programming published by the International Electrotechnical Commission (IEC).

By adopting FCL file format, instead using Matlab FIS proprietary format, fuzzy controls defined in FCL file format, can be used by any FCL-compliant fuzzy controller software, such as open source py-Fuzzy, which based on python language. jFuzzyLogic is also an open source solution and free to be utilized in our experiment. In developing countries such as Indonesia, this economical solution can be easily implemented. The use of FCL and python might be useful in the future for integration of this system in real world applications. Blender also supports python for animation scripting and game engine programming.

Input consists of 6 (six) probability values of six emotion classes. Each input has following three linguistic variables: low, medium and high, implemented using triangle MF. Input is categorized as low, when input value is between -0.4 and 0.4; medium when input value is between 0.1 and 0.9; and high, when input value is between 0.6 and 1.4, as depicted in Fig. 6.

While for the output, as a general rule, logic pair "1" is assigned for all of values listed as corresponding face control parameters (see Fig. 5). To illustrate more details on how linguistic variables are assigned for an output, please allow us to show one example first, namely EyeOpen L, which is left part of EyeOpen.R/L control. R/L here stands for "Right/Left". In our system, to maintain symmetric expression between left and right part of the face, L and R rules are identical. From face controls which are previously defined, EyeOpen L control should have logic pair 1 for sadness at -0.25; (disgust) at -0.12; (shame, joy, neutral) at 0; and (anger, fear) at 0.25. These assignments mean that for EyeOpen L control, expression of anger shares common facial appearance with fear; shame shares with (joy, neutral). Linguistic variables are sadness, disgust, shamejoyneutral and angerfear (see Fig. 7). All are implemented using triangle MF and Center Of Gravity (COG) defuzzification method. All of linguistic variables of inputs and outputs need to be related using rules. Rules will select which MF will be used in defuzzification stage. These relations are intuitive.

For example, rule IF (sadness IS high) THEN EyeOpen L IS ssadness means ssadness defuzzification map will be activated for EyeOpen L control, if probability of sadness is high. While for medium, the same map applied but the weight is reduced by half,

hence the rule in FCL is IF (sadness IS medium) THEN EyeOpen L IS sadness WITH 0.5. As a general rule for our fuzzy-based mechanism, for medium probability values, the weight is reduced by half or set to 0.5.

If all of probability values are low, MF for displaying neutral expression will be utilised, namely shamejoy-neutral, hence the rule is

IF (disgust IS low) AND (fear IS low) AND (joy IS low) AND (sadness IS low) AND (shame IS low) AND (anger IS low) THEN EyeOpen L IS shamejoyneutral. Table 5 shows all rules for EyeOpen L control.

FIS implementation of EyesDirection control is simpler. Fig. 8 depicts defuzzification mapping for EyesDirection. There are only two rules: when intensity of shame is high, shame will be selected and if intensity of shame is medium, same map is applied, however weight is reduced by half or set to 0.5. Other than these two conditions, output is set to default (0) which represents neutral facial expression. Table 6 shows all rules for EyesDirection control.

Triangle MF shown in Fig. 8 implies that intensity decrease of shame will increase value of EyesDirection control (using COG defuzzification), which move from -0.25 to 0, in other words, from "shame" to "rather shame" to "a bit shame" to "neutral" for eyes direction of face model. Analogous approaches using triangle MF apply to the rest of face controls.

III. EXPERIMENTS AND DISCUSSIONS

Previously, performance of NB text classifier for Indonesian text was conducted by [7, 40] using a portion of translated version of ISEAR dataset. Total number of Indonesian version of dataset is 1,240 text files, which consist of 5 (five) classes of emotion namely disgust (*jijik*), anger (*marah*), sadness (*sedih*), joy (*senang*), and fear (*takut*) and their number are 222, 263, 222, 311 and 222 respectively.

In our experiments, 6 (six) classes (anger, disgust, fear, joy, sadness, shame) of emotion text from original ISEAR dataset are used, which consist of total 3,000 text files, with each class has 500 items. Shame is included as an addition from our previous experiments.

Text is preprocessed as is and feature sets are formed based on word frequency using Bag-Of-Word (BOW) approach. To achieve a better measure of accuracy of NB text classifier, cross validation is performed. In our experiment using 10-fold cross-validation, the ISEAR dataset is randomly partitioned into 10 sub-samples. The cross-validation process is then repeated 10 times, with each process selects sub-sample randomly. For split ratio between training-set and validation set equals to 50:50, accuracy is 56.51%.

As inputs for Fuzzy Inference System to control face parameter, all of probability values output from NB text classifier are used. As shown in Fig. 9 and Fig. 10, facial expression of Ludwig displays not only strongest emotion, but a mixture of basic emotions. Text is not only conveying information, but also able to trigger emotional response in the reader (listener) or writer (speaker). This non-animated facial expres-

sion of Ludwig can be portrayed as a single spontaneous reaction immediately after "understanding" the text.

In our previous research, [39, 40] have conducted a small scale survey by asking human viewers about the appropriateness of generated facial expression from 5 (five) basic emotions in Indonesian. Twenty facial expressions of Ludwig along with 20 (twenty) corresponding Indonesian sentences, were showed to 100 (one hundred) respondents. They should choose one from two possible answers; "Yes, it is an appropriate expression" or "No". Survey indicated that total number of "Yes" answer was 1,328 and "No" answer was 672, which equal to 66.4% accuracy.

In our current experiments, Fig. 9 and Fig. 10 show samples of facial expression with their corresponding text input. Arrow with (i) indicates text classification process using NB classifier and the number next to the emotion class is the probability value of each emotion class which text belongs to, while arrow with (ii) indicates fuzzy inference mechanism which control facial appearance of life-like virtual character and the number next to face control name is the value of corresponding face control (see Fig. 1 for process (i) and (ii)).

These text input are unseen sentences (not from-training set), taken from Internet news. In Fig. 9 Ludwig looks somewhat in sadness and fear (worry?) as a result from emotions blending. Sentence in Fig. 10 is taken from Yahoo sports news and generate smiling face, which represents rather joy.

As baseline visual comparison, Fig. 11 and Fig. 12 depict facial expressions of basic emotions using sentences taken from training set. Please note, that in this paper, facial expression of shame is added, which can be seen in Fig. 11. These figures demonstrate that facial expressions of life-like virtual character are displayed as expected.

IV. CONCLUSIONS AND FUTURE WORKS

Using simple text classifier such as Naïve Bayes, combined with Fuzzy Inference System Mamdani, emotion representations can be displayed in the form of facial expressions of a model. Facial expressions are displayed from a mixture of emotions.

The reason why in this experiment, original English version of ISEAR dataset is chosen, not Indonesian translated version, because after some experiments using these two datasets, we observed that the accuracy of text classifier for emotion class is not high. Certainly the text classifier module in our proposed system can be substituted by another text classifier other than NB which may provide a better accuracy. Research to achieve better accuracy for classifying emotional content of text and evaluate its impact on facial expression is left for our future investigation.

For English text, there are some readily available resources such as semantic tools provided by NLTK, WordNet, and ConceptNet, need to be explored. They are accessible using python language [42, 43, 44]. We intend to improve the accuracy of text classifier because in our proposed system, the accuracy of text classifier

might have big impact on the facial expression.

For application to life-like virtual character in animation or game environment, the proposed system needs additional method to animate facial expressions smoothly, which able to show the dynamics of emotions.

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TABLE 1.
SAMPLE OF ISEAR DATASET

Emotion	Sentence
Joy	After my girlfriend had taken her exam, we went to her parent's place.
Sadness	My grandmother died.
Fear	At the dentist's, waiting for my turn to come.
Anger	Having a fight with a class mate.
Disgust	When I was weeding the garden I found a lizard in my hand.
Shame	Cheating to get the best grade on a test in 7th grade.
Guilt	I had a quarrel with near persons. I said many ill-considered things and I regretted it when it was too late.

TABLE 2.
BASIC EMOTIONS CLASSIFICATION

Psychologist	Basic emotions
Plutchik	Anger, anticipation, trust disgust, joy, fear, sadness, surprise
Ekman, Friesen, Ellsworth	Anger, disgust, fear, joy, sadness, surprise
Frijda	Desire, happiness, interest, surprise, wonder, sorrow
Izard	Anger, contempt, disgust, distress, fear, guilt, interest, joy, shame, surprise
James	Fear, grief, love, rage
Mowrer	Pain, pleasure
Oatley and Johnson-Laird	Anger, disgust, anxiety, happiness, sadness

TABLE 3.
FACIAL EXPRESSIONS OF BASIC EMOTIONS [31]

No	Basic emotions	Textual description of facial expressions
1	Joy	The eyebrows are relaxed. The mouth is open and the mouth corners pulled back toward the ears.
2	Sadness	The inner eyebrows are bent upward. The eyes are slightly closed. The mouth is relaxed.
3	Fear	The eyebrows are raised and pulled together. The inner eyebrows are bent upward. The eyes are tense and alert.
4	Anger	The inner eyebrows are pulled downward and together. The eyes are wide open. The lips are pressed against each other or opened to expose the teeth.
5	Disgust	The eyebrows and eyelids are relaxed. The upper lip is raised and curled, often asymmetrically.
6	Surprise	The eyebrows are raised. The upper eyelids are wide open, the lower relaxed. The jaw is opened.

TABLE 4.
OPERATING PARAMETER VALUES OF LUDWIG'S FACE\

FaceControl	Lower	Upper
EyesDirection	-0.25 (look down)	0.00 (straight)
BrowPosition.R/L	-0.25	0.25
BrowEmotion.R/L	0.00	0.25
BrowWrinkle	-0.25 -0.25	0.25 0.25
EyeOpen	(close)	(open eyed)
Sneer.R/L	0.00 (neutral)	0.25 (sneer)
MouthOpen	0.00 (open)	0.25 (close)
MouthSmile.R/L	-0.25 (frown/down)	0.25 (smile/up)

TABLE 5.
RULES FOR EYEOPEN L

RULE 1: IF (disgust IS low) AND (fear IS low) AND (joy IS low) AND (sadness IS low) AND (shame IS low) AND (anger IS low) THEN EyeOpen L IS shamejoyneutral;
RULE 2: IF (fear IS high) OR (anger IS high) THEN EyeOpen L IS angerfear;
RULE 3: IF (joy IS high) OR (shame IS high) THEN EyeOpen L IS shamejoyneutral;
RULE 4: IF (sadness IS high) THEN EyeOpen L IS ssadness;
RULE 5: IF (disgust IS high) THEN EyeOpen L IS ddisgust;
RULE 6: IF (sadness IS medium) THEN EyeOpen L IS ssadness WITH 0.5;
RULE 7: IF (joy IS medium) OR (shame IS medium) THEN EyeOpen L IS shamejoyneutral WITH 0.5;
RULE 8: IF (anger IS medium) OR (fear IS medium) THEN EyeOpen L IS angerfear WITH 0.5;
RULE 9: IF (disgust IS medium) THEN EyeOpen L IS ddisgust with 0.5;

TABLE 6.
RULES FOR EyesDirection

RULE 1: IF (shame IS high) THEN EyesDirection IS sshame;
RULE 2: IF (shame IS medium) THEN EyesDirection IS sshame WITH 0.5;

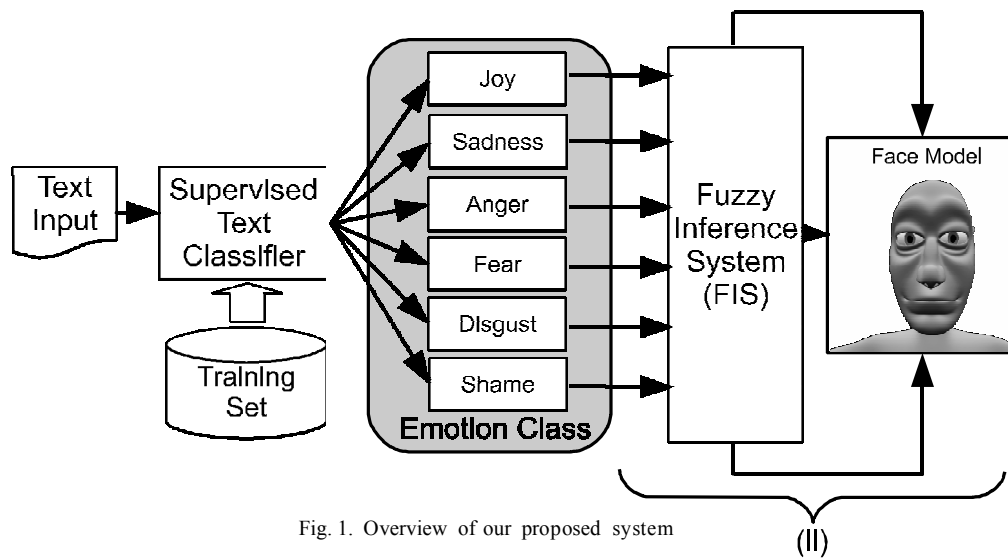


Fig. 1. Overview of our proposed system

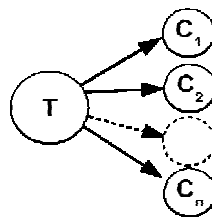


Fig. 2. Graph representation of NB classifier

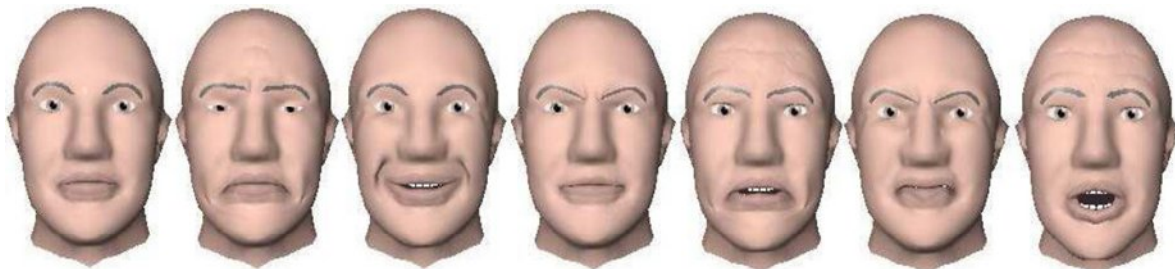


Fig. 3. Facial expressions of basic emotions, taken from [23]: neutral, sadness, joy, anger, fear, disgust, surprise (from left to right).

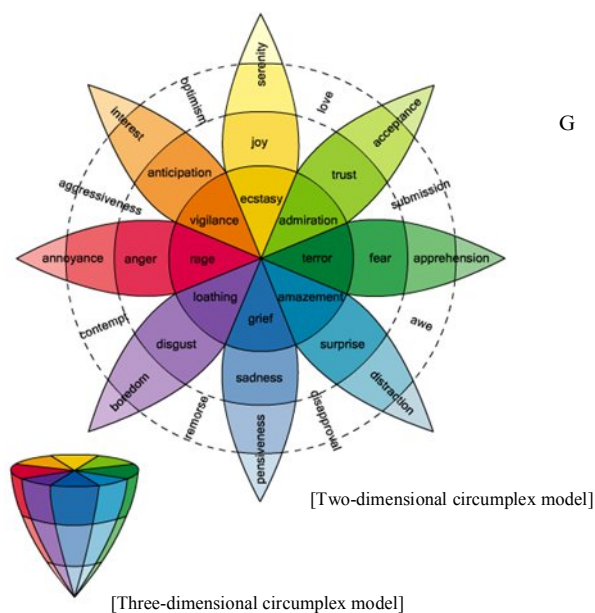


Fig. 4. Plutchik's wheel of emotion

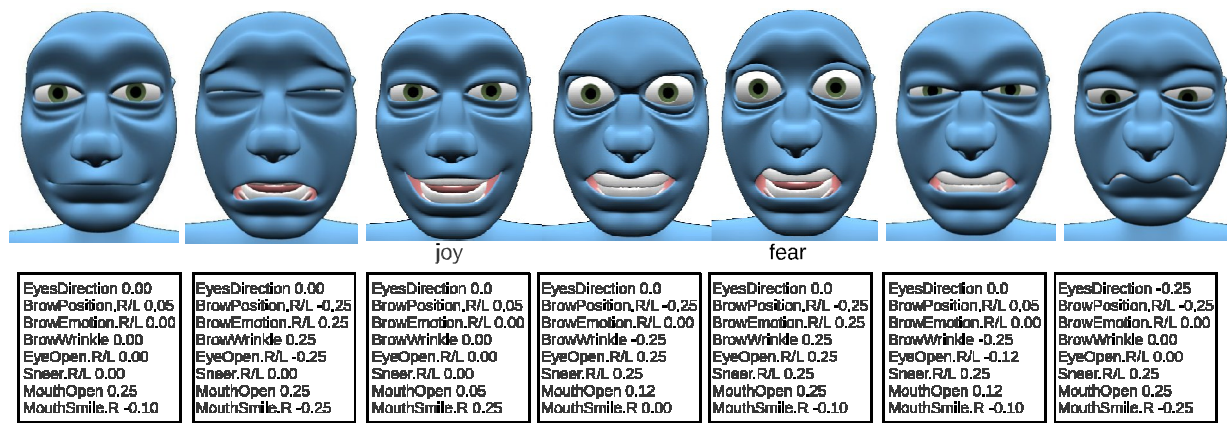


Fig. 5. Facial expressions of Ludwig in basic emotions and their corresponding face control parameters

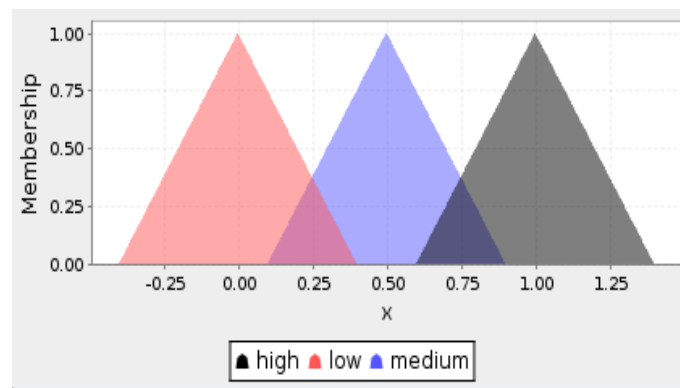


Fig. 6. Membership Function (MF) of input

EyeOpen_L

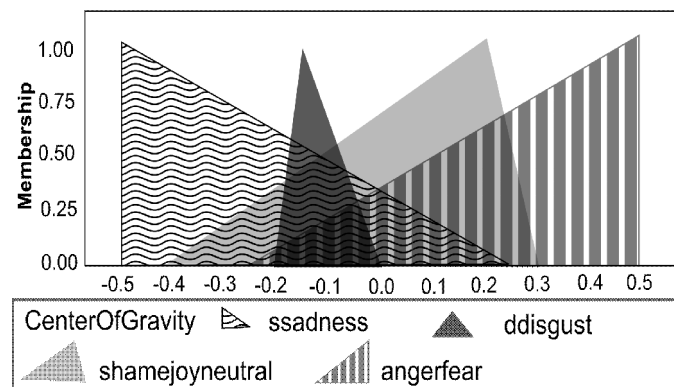


Fig. 7. MF of output EyeOpen L

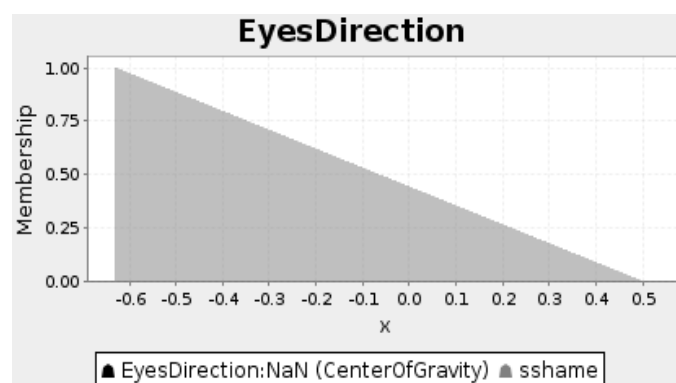


Fig. 8. Membership function of output EyesDirection

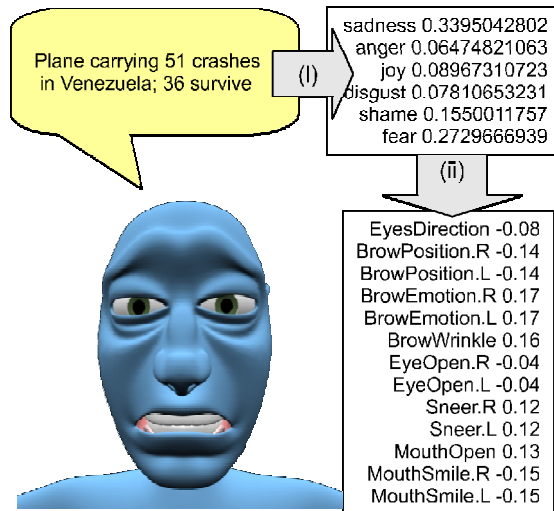


Fig. 9. Ludwig looks somewhat in sadness and fear(worry)

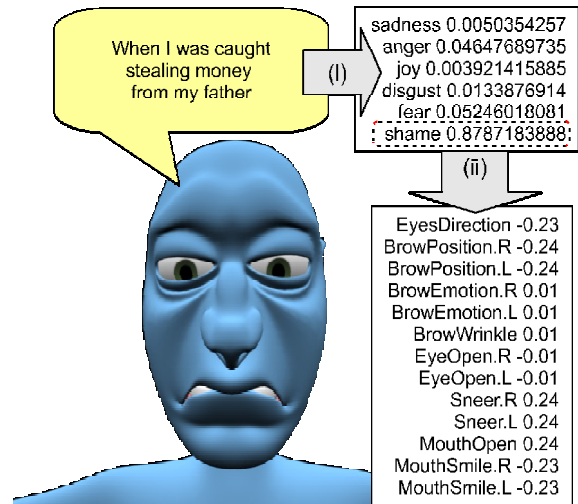


Fig. 11. Shame facial expression with its corresponding sentence taken from training data

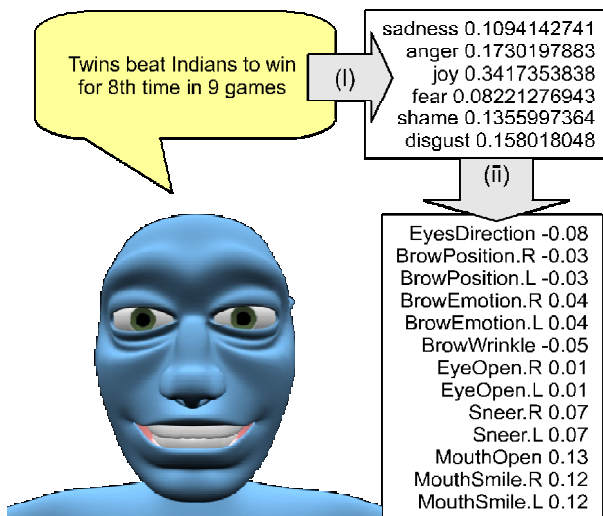


Fig. 10. Unseen sentence generates rather joy

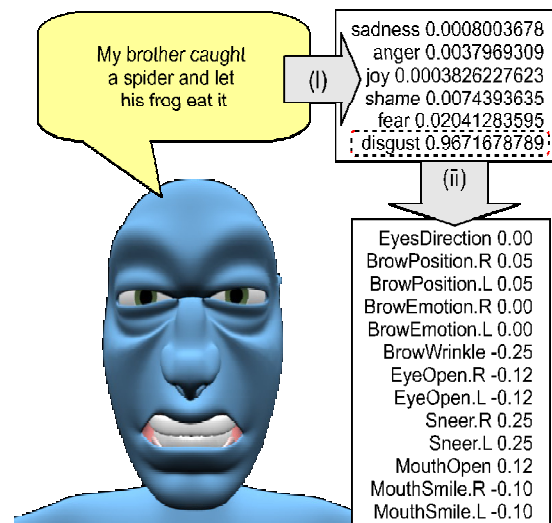


Fig. 12. Disgust facial expression with its corresponding sentence taken from training data set