修士学位請求論文

# AffectIM: An Avatar-based Instant Messaging System Employing Rule-based Affect Sensing from Text

# AffectIM：テキストからのルールに基づく感情抽出を用いるアバタ付きインスタントメセージング・システム

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# Abstract

Social interactions among people play an important role in the establishment of genuine interpersonal relationships and communities. We convey information through multiple expressive channels, such as natural language, intonation, gaze, facial expressions, gestures, and body language. Recently, computer-mediated communication became a popular way of interaction, especially among young people. However, it lacks the mentioned signals of face-to-face communication. In our work, we concentrate on affect recognition from text in Instant Messaging (IM) to automate expressive channels and to improve social interactivity of this media type.

To analyse affect communicated through written language, researchers in the area of natural language processing proposed a variety of approaches, methodologies and techniques. However, the weakness of most affect recognition systems integrated with chat or e-mail browsers is, that they do not take into consideration crucial aspects of informal online conversation, such as evolving language or linguistic and interactional features. IM users are continuously developing their own language, the motivations behind which are speed and less typing. The understanding of this evolving language by people and syntactical parsers is the main problem in messaging.

In order to facilitate sensitive and expressive communication in computer-mediated environments, we introduced a novel syntactical rule-based approach to affect recognition from text. The developed Affect Analysis Model was designed to handle not only grammatically and syntactically correct textual input, but also informal messages written in abbreviated or expressive manner. In contrast to machine-learning based approaches, for which detection of emotions on a sentence level still remains a challenge, the proposed rule-based approach processes each sentence in sequential stages, including symbolic cue processing, detection and transformation of abbreviations, sentence parsing, and word/phrase/sentence-level analyses.

Since the purpose of affect recognition in an IM system is to relate text to avatar emotional expressions, affect categories were confined to those that can be visually expressed and easily understood by users: ‘anger’, ‘disgust’, ‘fear’, ‘guilt’, ‘interest’, ‘joy’, ‘sadness’, ‘shame’, and ‘surprise’ Additionally, the information related to communicative behaviour (e.g. ‘greeting’, ‘thanks’, ‘posing a question’, ‘congratulation’, and ‘farewell’), directly dependent on context and carrying significant communicative power, can be derived from online conversations.

To support the handling of abbreviated language and the interpretation of affective features of linguistic concepts, a special Affect database, containing emoticons and abbreviations, interjections, modifiers, direct and indirect emotion-related words (adjectives, adverbs, nouns,

and verbs), and words standing for communicative functions, was created. For accumulation of relevant and most often used emoticons and abbreviations, we employed five online dictionaries dedicated to and describing such data. Words conveying affective content directly or indirectly were taken from the source of affective lexicon, WordNet-Affect. Each database entry was annotated, depending on its role, with the emotion category with intensity, or communicative function category, or modifier coefficient.

The main advantage of the proposed rule-based methodology is its flexibility allowing to handle the evolving language of online communications; to represent the affective features of words, phrases, clauses and sentences as a vector; to cover such linguistic aspects as negation, modality, and conditionality; to consider syntactic relations and dependences between words in a sentence, or between clauses in compound, complex, or complex-compound sentences; and to introduce new processing rules to the developed Affect Analysis Model. While affect sensing, each analyzed sentence is automatically annotated with emotion (or neutral) label, and numerical value, which indicates the degree of emotion intensity. Furthermore, the information related to communicative behaviour is identified.

The evaluation of the Affect Analysis Model algorithm showed promising results regarding its capability to recognize affective information in text from an existing corpus of informal online communication. In a study based on 160 sentences, the system result agreed with at least two out of three human annotators in 70% of the cases.

In order to enrich the user's experience in online communication, make it enjoyable, exciting and fun, we realized a web-based IM application, AffectIM, and endowed it with the emotional intelligence by integrating with the developed Affect Analysis Model. AffectIM supports online communication, allows users to see the conversation flow in three modes (plain text, transcribed text, or text annotated with emotion), and visualizes the communicated emotions, emotion distribution and emotion dynamics. To support visual reflection of sensed affective information, we have designed and animated two 2D cartoon-like avatars (graphical representations of a user) performing various expressive patterns (emotions, social behavior, and natural idle movements), contributing thus to greater interactivity.

During our 20-user experiment with three interfaces of AffectIM system (automatic, manual, and random conditions) we got many valuable results and feedbacks, and investigated new ways of improvements. The data obtained showed that the developed emotion recognition engine worked with good level of reliability, so that there was no significant difference between system providing automatic emotion sensing from text and system with manual control of emotional behavior of avatars (so called "gold standard"). It is evident that AffectIM would benefit from integration of both these functions in one interface, where they can complement each other and provide user with the ability to select between two modes (automatic or manual control of emotion expressions) depending on type and sensitivity of conversation.

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# Chapter 1

# Introduction

## 1.1 Emotions and Their Unique Role in Social Interactions

"*...emotion or passion of the soul is a confused idea.*"
Spinoza

If I were ever asked to portray such phenomena as emotions and feelings with only one stroke, I would draw an allegoric parallel with *water*, singular, multifarious, and indispensable to life.

Imagine possible forms of water subjected by internal and external factors. Would thunderstorm or tsunami, destructive ocean wave caused by an earthquake or volcanic eruption, resemble anger person, ready to fight or sweeping away everything on his way? Would the "blind rain", when the drops of intermittent rain sparkle in the sunlight, forming colorful rainbow, look like tears of happiness or smile through tears; or steady downpour from the dull sky – like tears of resentment or sadness? Would clinking streamlet in a fresh forest correspond to cheerfulness, and waterfall producing splashes flying in all directions – to elation? We might even find emotional associations with fog, blizzard, unhurried dance of snowflakes, melted ice, etc.

Emotions and feelings accompany us throughout the span of our lives and color the way we build and maintain the basis for interactions with people in a society. In a real world, whenever one person interacts with another, both observe, perceive and interpret each other's emotional expressions communicated through subtle details of contraction of facial muscles, tints of facial skin, variations of voice intonation, eye movements, gestures, and body postures. Unique development and environment shape the composition and dynamics of the emotional reactions in each individual.

Emotions have long been a central interest in philosophical, psychological, and sociological studies, producing thus fruitful thoughts, discussions and lines of theories. Nevertheless, the crucial question "what emotions are" has been causing heated arguments and a lack of agreement among scientists studying these phenomena [71].

Great psychologist and philosopher Aristotle considered human emotions an important topic. He argued that the rational and irrational parts of human soul necessarily form a unity, and this is particularly true of emotions that involve a cognitive element, including beliefs and expectations about one's situation, as well as physical sensations. In the "Rhetoric" [66], Aristotle reason about strong moral belief about how others should behave as a main characteristic component of many emotions. Another distinguished philosopher, Spinoza, introduced theory of emotions in his major work – "Ethics" [73]. According to Spinoza, emotions are flawed thoughts about the world, misunderstandings, and all emotions are ultimately defined by reference to pleasure and pain. He characterized "passive" emotions as originated from outside of us, and "active" ones – as outcome of our own natures and a pleasurable sense of heightened activity. Hume [30] was the first modern philosopher to give serious attention to the role ideas and beliefs play in generating emotions. Suggesting the idea that emotions are always felt "about" or "toward" objects, and classifying emotions into two general categories – "direct" and "indirect" – depending on causes and conditions associated with emotions, Hume made an important contribution to the history of philosophy.

By the end of the nineteenth century James and Freud had written extensively on different aspects of emotion and given emotion a privileged place in scientific discourse.

James' essay "What is an Emotion?" [33] is one of the classic works which give rise to contradictious points of view (either agreement or reaction) and form the background for today's studies of emotions. The core of James-Lange theory [34] is a definition of emotion as the perception of physiological disturbances caused by our awareness of events and objects in our environment. The main focus of this theory is physical sensations. James stated that we would be only in a "cold and neutral state of intellectual perception" if we abstracted all the characteristic bodily symptoms from our emotional experience.

Freud in his psychoanalytical theory [24] ambiguously described an emotion as just a "feeling-tone" or as a complex that includes not only a feeling (an affect), but also an *instinct* that motivates it and an *idea* that directs it towards an object.

According to American philosopher Dewey, who incorporated some elements from James's theory into his own theory [19], there are three components defining emotions: feeling, purposeful behavior, and an object that has an emotional quality. He said that "the emotion is always "about" or "toward" something; it is "at" or "on account of" something, and this prepositional reference is an integral phase of the single pulse of emotion."

In recent decades, interest in emotions in psychology has virtually exploded, with ambitious theories exploring all sorts of new directions. The proposed theories considered the physiological, cognitive, behavioral, and other, more sophisticated aspects of emotion.

Two elements – the physiological component of arousal and a "cognitive" component that determines how emotions are labeled and discriminated among – are included in the theory of emotion proposed by Schachter and Singer [68].

As shown in the work of Ekman [20], six so called "basic" emotions – fear, anger, sadness, disgust, surprise, and happiness – have been found to be universal emotions in terms of their facial expression and recognizability. Ekman has refined his research on facial expressions and established a precise monitoring and measurement system that has become standard in psychology proving the universality of facial recognition.

Empirical psychologist Frijda accentuated the functional role of emotions [25]. He argued that emotions serve the functions of preserving and enhancing life.

Lazarus was one of the initiators of the appraisal theory, according to which an emotion is an appraisal of the world. This theory is uncompromisingly devoted to the conceptual nature of emotions concerned with cognitive contents [38]. In [72], Solomon defended his cognitive theory of emotions in which evaluative *judgments* play an essential role: "If I do not believe that I have somehow been wronged, I cannot be angry (though I might be upset, or sad). Similarly, if I cannot praise my lover, I cannot be in love… If I do not find my situation awkward, I cannot be ashamed or embarrassed. If I do not judge that I have suffered a loss, I cannot be sad or jealous…To have an emotion is to hold a normative judgment about one's situation."

Rule-base mechanisms for cognitive generation of emotions are provided by the OCC [56] and Roseman [67] appraisal theories.

Izard [31] proposed that there are four types of elicitors of emotion in humans: neural, sensorimotor, motivational, and cognitive.

The exciting new discoveries in neurobiology and the tremendous impact these are having on the very conception of emotion and emotional feelings are represented by Damasio in [15]. He argues that "the fabric of our minds and of our behavior is woven around continuous cycles of emotions followed by feelings that become known and beget new emotions, a running polyphony that underscores and punctuates specific thoughts in our minds and actions in our behavior" and that "… consciousness is the critical biological function that allows us to know sorrow or know joy, to know suffering or know pleasure, to sense embarrassment or pride, to grieve for lost love or lost life".

The essentialness of emotions to social life is manifested by the rich history of theories and debates about emotions and their nature. We can hardly disagree with the following Lutz's statement: "… the concepts of emotion can more profitably be viewed as serving complex communicative, moral, and cultural purposes rather than simply as labels for internal states whose nature or essence is presumed to be universal. The pragmatic and associative networks of meaning in which each emotion word is embedded are extremely rich ones. The complex meaning of each emotion word is the result of the important role those words play in articulating the full range of a people's cultural values, social relations, and economic circumstances. Talk about emotions is simultaneous talk about society – about power and politics, about kinship and marriage, about normality and deviance." [46].

The role and importance of emotions in the regulation of social life should not be underestimated. In a global vision, it is like the significance of water as one of the variety of ways to regulate the harmony in the nature.

## 1.2 Research Motivation and Objectives

> "*People in virtual communities use words on screens to exchange pleasantries and argue, engage in intellectual discourse, conduct commerce, exchange knowledge, share emotional support, make plans, brainstorm, gossip, feud, fall in love, find friends and lose them, play games, flirt, create a little high art and a lot of idle talk. People in virtual communities do just about everything people do in real life, but we leave our bodies behind. You can't kiss anybody and nobody can punch you in the nose, but a lot can happen within those boundaries. To the millions who have been drawn into it, the richness and vitality of computer-linked cultures is attractive, even addictive.*"
>
> Rheingold Howard

Social interaction among people is an essential part of every society, and a strong foundation for the development and self-actualization of a person, and for the establishment of genuine interpersonal relationships and communities. In everyday life we communicate with each other through multiple informative channels. People in virtual environments tend to interact in a social way too. However, computer-mediated communication lacks such signals of face-to-face communication as spoken language, intonation, gaze, facial expressions, gestures, and body language.

The online world of computer-mediated communication is such an environment where people can virtually remain in touch with their relatives and friends to exchange experiences, share opinions and feelings, and satisfy their social need of interpersonal communication. The construction of human-human online environments and human-computer systems [14] might greatly benefit from consideration of human emotions since affect is an important component of effective social interaction. Research conducted by Peris et al. [60] argues that "people who use online chats are not only perfectly able to fulfil their social needs in the real world, but they consider online relationships as real as face-to-face relationships". Authors point to the fact that online chats may stimulate rather than inhibit social relations, and chat users seem to find a media for rich, intense, and interesting experiences. Results of study described in [29] lend support to authors' hypothesis that there is a positive relationship between the amount of IM use and verbal, affective, and social intimacy; and indicated that frequent conversation via IM actually encourages the desire to meet face-to-face, reinforcing thus personal interaction.

In our research we focus on affect recognition from written language in order to facilitate sensitive and expressive communication in computer-mediated environments. The ability to express emotions in text and self-presentation are very important for a social and friendly atmosphere. Trends show that messaging text is often enriched by symbolic conventions (emoticons, capital letters etc.) to be more expressive. Despite the playful nature of these conventions, the expressions of emotion conveyed are, according to Reid [65], "not in any way thought to be shallow or ephemeral". The results of study described in [18] imply that emoticons can serve as nonverbal surrogates for visual cues in face-to-face communication and certainly have an impact on online message interpretation.

The motivation behind our approach is to enrich social interactivity and emotional expressiveness of real-time messaging, where a machine is used as a communication channel connecting people and transmitting human emotions. Here, a key issue is to provide the automation of multiple expressive means so that the user does not have to worry about visual self-presentation as in standard Instant Messaging (IM) systems, but can focus on the textual content of the conversation. According to Picard [61], "the basic requirement for a computer to have the ability to express emotions is that the machine have channels of communication such as voice or image, and an ability to communicate affective information over those channels…".

The main objectives of our research are:

— To create affect recognition system integrated with IM capable of recognition of emotions and communicative behavior conveyed through online text messages

— To support the automation of multiple expressive channels on the basis of textual affective information

## 1.3 Background and Related Works

"*Language is about something, does something, and is something in itself; the content and conduct of emotional communication are integrally related.*"

Donald Brenneis

In the past decade, issues of recognition, interpretation and representation of affect have been extensively investigated by researchers in the field of affective computing [61]. A wide range of modalities has been considered, including affect in speech, facial display, posture, and physiological activity. The necessity to design intelligent user interfaces and to create rich mediating environments for social interactions was a strong incentive for many researchers to analyse natural language with regard to affective information.

Since the focus of our research is two-fold (affect recognition and visualization), in next two subsections we will discuss related works on sensing of affective content and on its visualization.

### 1.3.1 Recognition of Affective Content Conveyed through Written Language

Recently, textual information is gaining increased attention by researchers interested in studying different kinds of affective phenomena, including sentiment analysis, subjectivity and emotions. In order to analyse affect communicated through written language, researchers in the area of natural language processing proposed a variety of approaches, methodologies and techniques.

WordNet-Affect, a linguistic resource for the lexical representation of affective knowledge, was created by Strapparava and Valitutti [74] with the aim to support applications relying on affective language recognition and generation. The affective concepts in this database are provided with the semantic labels (*a-labels*), the examples of which are shown in Table 1.1.

Table 1.1 Examples of affective words with A-labels from WordNet-Affect [74]

| A-Label | Affective words |
|---|---|
| Emotion | “anger”; “fear” |
| Mood | “animosity”; “amiable” |
| Trait | “aggressiveness”; “competitive” |
| Cognitive State | “confusion”; “dazed” |
| Physical State | “illness”; “all_in” |
| Hedonic Signal | “hurt”; “suffering” |
| Emotion-eliciting Situation | “awkwardness”; “out_of_danger” |
| Emotional Response | “cold_sweat”; “tremble” |
| Behaviour | “offense”; “inhibited” |
| Attitude | “intolerance”; “defensive” |
| Sensation | “coldness”; “feel” |

Automatic textual emotion recognition and its visualization by kinetic typography (text animation) are described in [75]. In order to analyse affective content, the authors were using not only affective words from WordNet-Affect, but also an indirect affective lexicon derived from the evaluation of the semantic similarity between generic terms and affective lexical concepts using Latent Semantic Analysis technique. The main point here is the argumentation that all words can potentially convey affective meaning due to their semantic relation with emotional concepts. Examples of the results of analysis of news titles are listed in the Table 1.2.

Table 1.2 Some news titles and the respective emotional categories [75]

| News title | Emotional category | Affective weight | Word with highest affective weight |
|---|---|---|---|
| Review: ‘King Kong’ a giant pleasure | Joy | 0.78 | pleasure#n |
| Romania: helicopter crash kills four people | Fear | 0.67 | crash#v |
| Record sales suffer steep decline | Sadness | 0.61 | suffer#v |
| Dead whale in Greenpeace protest | Anger | 0.69 | protest#v |

Kamps and Marx [36] investigated measures for affective or emotive aspects of meaning obtained from the structure of the WordNet lexical database [49]. Since the meaning of a concept in WordNet is determined by its place relative to other concepts, authors decided to evaluate individual words (specifically, adjectives) by determining their relation (or distance) to the words ‘good’ and ‘bad’. To establish the relatedness of two words, the main attention was paid to synonymy relation that connects words with similar meaning. The minimal path-length (MPL) was considered as a straightforward generalization of such relation. For example, MPL(good; proper) is 2; MPL(good; neat) is 3; MPL(good; noble) is 4. On the word-level analysis, authors described the functions assigning values in the interval [-1;1] based on the MPLs from adjectives ‘good’ and ‘bad’. The described research resulted in finding the cluster of 5410 attitude-carrying adjectives, which comprise 25% of the adjectives in WordNet. As to evaluation of larger textual units, a straightforward aggregation procedure was implemented. Shortly, text was represented as a bag of words, then, each of these individual words was evaluated, and their scores were simply added up.

To classify sentiment and affect represented in text, methods employing Pointwise-Mutual Information calculation were introduced [64,77]. Turney [77] presented an unsupervised learning algorithm for classifying reviews as recommended or not recommended based on estimation of average of semantic orientation of phrases. First, part-of-speech tagger identifies phrases containing adjectives or adverbs. Next, semantic orientation of each phrase is estimated based on the following rule: a phrase has positive or negative semantic orientation when there are good (e.g., “romantic ambience”) or bad (e.g., “horrific events”) associations, respectively. To measure the similarity of pairs of words, the PMI-IR algorithm (Pointwise Mutual Information and Information Retrieval) is employed. More specifically, a phrase is numerically rated by taking the mutual information between the given phrase and the word “excellent” and subtracting the mutual information between the given phrase and the word “poor”. After averaging the results from phrase-level, the given review is assigned to either recommended or non-recommended class. Proposed algorithm achieved an average accuracy of 74% while analysis of 410 highly opinionated reviews sampled from four different domains. However, the main limitations of this work include concentration on phrase-level analysis, disregard of syntactic relations and dependencies, and the time required for queries.

In contrast to Turney's work [77], Pang et al. [59] utilized several completely prior-knowledge-free supervised machine-learning methods, with the goal of classification of film reviews into "positive" and "negative". Authors found out that for more accurate classification some form of discourse analysis is necessary, or at least some way of determining the focus of each sentence since, according to Turney [77], "the whole is not necessarily the sum of the parts".

In [58], Owsley et al. argued that, since people use varied language to describe objects and events in different domains, the accuracy of affect classification of blog documents can be increased through generation of domain specific sentiment classifiers.

Wilson et al. [79] presented experiments in which they automatically distinguish prior and contextual polarity of individual words and phrases in sentiment expressions, in contrast to classifying documents by their overall sentiment.

An approach to analysing affect content in free text using fuzzy logic techniques was proposed by Subasic and Huettner [76]. The fuzzy semantic typing involves the followings: isolating a vocabulary of words belonging to a metalinguistic domain (here, affect or emotion); using multiple categorizations and scalar metrics to represent the meaning of each word in that domain; computing profiles for texts based on the categorizations and scores of their component domain words; and manipulating the profiles to visualize the texts. Dealing with lexical ambiguity, authors allowed a word to belong to multiple semantic categories. Two main characteristics were assigned to lexicon entries: (1) degree of relatedness (centrality) between words and their various categories; (2) numerical intensities, which represent the strength of the affect level described by particular word. For example, verb "emasculate" belongs to "weakness", "lack", and "violence" categories with the centralities 0.7, 0.4, and 0.3, correspondingly. Intensity degrees, like centrality degrees, range from 0 to 1 by increments of 0.1. While processing the document, affect words are tagged, and the fuzzy logic part of the system handles them by using fuzzy combination operators, set extension operators and a fuzzy thesaurus to analyze fuzzy sets representing affects. Authors claim that using the developed algorithm (see Figure 1.1), it is possible to generate the affect set for any document.

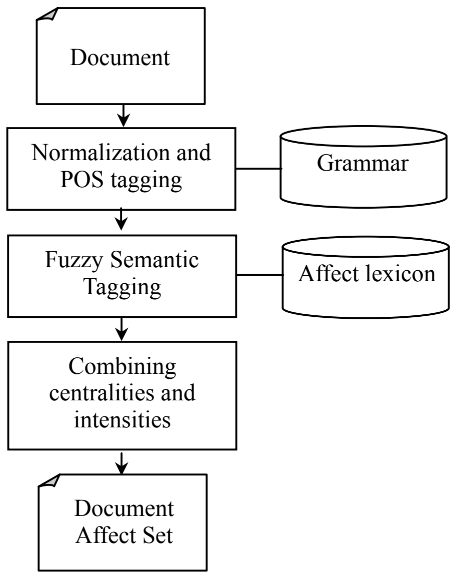


Figure 1.1 Generation of the document affect set, a fuzzy set representing the affective content of a document [76]

Research on mining the WordNet for fuzzy sentiment was conducted by Andreevskaia and Bergler [3]. They proposed a method for extracting sentiment-bearing adjectives from Word-Net using the developed dictionary-based Sentiment Tag Extraction Program named STEP. The approach based on the fuzzy logic is used to assign fuzzy sentiment tags (positive, negative, or neutral labels) and a degree of centrality of the annotated words to the sentiment category to all words in WordNet. The STEP algorithm works as follows: (1) a small set of seed words of known value (positive or negative) is supplemented by adding their synonyms, antonyms and hyponyms found in WordNet; (2) the system processes all WordNet glosses and identifies the entries containing in their definitions the sentiment-bearing words from the extended list and adds these head words to the corresponding category; (3) clean-up pass is performed to partially disambiguate the identified entries with part-of-speech tagger and to filter out words with contradicting assignments. Using multiple STEP runs, the list containing 7,814 positive and negative English adjectives was produced and cross-validated with an average accuracy of 66.5%.

Kim and Hovy [37] developed an automatic algorithm for classifying opinion-bearing and non-opinion-bearing words, and described a method for the detection of sentence-level opinion. They built a classifier that identifies all sentences expressing valence in a given text, using such strong markers of opinion as certain modal verbs (e.g. “should”, “must”) and adjectives and adverbs (e.g. “better”, “unfair”, “desirable”). According to their proposal, words are classified as opinion-bearing depending on the degree of closeness to manually chosen sets of opinion-bearing words in WordNet. As to the sentence valence, it was measured on the basis of presence of a single strong valence word.

Statistical language modelling techniques have been also applied by researchers to analyse moods conveyed through online diary-like posts [41,48,50]. However, machine learning approaches (so called “bag-of-words” approaches) to affect classification in text suffer from limitations such as: necessity of large amounts of data to gather meaningful statistics and to be reliable; neglect of negation and condition constructions; and disregard of syntactical relations and dependencies in sentences.

Some researchers employed a keyword spotting technique to recognize emotion from text [54,75] or expressed in a multi-modal way (for example, speech signals along with textual content [80]). The system proposed by Olveres et al. [54] infers different emotions from textual input and automatically displays them on the 3D avatar appearance in a chat environment. This system uses a shallow Natural Language Parser for keyword spotting, modifier identification, phrase length measurement and emoticon spotting. The main words recognized are adjectives that give a clearer idea of expressed emotion. However, the use of a pure word-level analysis model cannot handle cases where affect is expressed by phrases requiring complex phrase/sentence-level analyses, since words are interrelated and influence each other’s affect-related interpretation (like in the sentence “*I use the ability to breathe without guilt or worry*”), or when a sentence carries affect through underlying meaning (for example, “*I punched my car radio, and my knuckle is now bleeding*”).

Advanced approaches targeting at textual affect recognition performed at the sentence-level are described in [9,42,52]. The lexical, grammatical approach introduced by Mulder et al. [52] focused on the propagation of affect towards an object.

Boucouvalas [9] developed the Text-to-Emotion Engine based on word tagging and analysis of sentences. The proposed system uses a small set of emotions, the six “basic” types defined by Ekman [21]. The emotion extraction engine can analyse input text from a chat environment, identify the emotion communicated, and deliver the parameters necessary to invoke an appropriate expressive image on screen to the communicating user display (Figure 1.2).


Figure 1.2 Screen view of 'Expressive Interface' [9]

However, the proposed system employs the parser that generates emotional output only if an emotional word refers to the person himself/herself and the sentence is in present continuous or present perfect continuous tense. We think that such limitations greatly narrow the potential of textual emotion recognition. As the result, sentences like "*Onion pie is disgusting*" and "*It was the most joyous feeling!*" are disregarded by the parser despite the fact that they evidently carry affect.

An approach for understanding the underlying semantics of language using large-scale real-world commonsense knowledge was proposed by Liu et al. [42], who incorporated the created affect sensing engine into an affectively responsive email composer called EmpathyBuddy (Figure 1.3). The architecture of the affect sensing engine includes the Model Trainer and the Text Analyzer.

The Model Trainer has three sequential modules:

1. Linguistic Processing Suite including part-of-speech tagging, phrase chunking, constituent parsing, subject-verb-object-object identification, and semantic class generalization;
2. Affective Commonsense Filter and Grounder (affective commonsense is filtered from the whole corpus using emotion ground keywords; and emotion keywords are tagged with "grounds" in preparation for training the models);
3. Propagation Trainer propagating the affect valence from the emotion grounds to concepts related through commonsense relations.

Text Analyzer architecture represents five sequential modules: Text Segmenter; Linguistic Processing Suite; Story Interpreter; Smoother; and Expressor. Text is first segmented into paragraphs, sentences, and independent clauses. Each parsed sentence is evaluated with prepared models and weighted scoring function generates a six-tuple score. Each sentence is annotated with one of the six "basic" emotions [21], or "neutral", and the total score. The visual feedback to a user is given through simplified emotional faces (Figure 1.3).


Figure 1.3 EmpathyBuddy email agent and user scenario [42]

Style and level of formalism of written natural language differ greatly depending on situation. In news, reports, scientific papers etc., text is syntactically correct and written in a formal style, while in private correspondence, online messaging, and blogs, text is informal and may include special symbols, emoticons, abbreviations and acronyms.

The weakness of most affect recognition systems integrated with a chat or e-mail browser, however, is that they do not take into account crucial aspects of informal online conversation such as its specific style and evolving language. In order to account for the peculiarity of this medium, and to ensure satisfactory results on real examples, we investigated style, linguistic and interactional features of online conversations (see Chapter 2 for details), and considered them while constructing our affect analysis model.

### 1.3.2 Visualization of Affective Information

Recently, a wide variety of approaches to visualizing the affective content of written discourses and documents can be observed. The underlying idea is to associate each emotion with a particular pattern of expressive reaction. It has been demonstrated that affect can be represented by means of color, expressive and moving text, static or animated emoticons (simplified emotional faces), cartoon-like characters or human-like avatars, and images of human faces with emotional expression.

In [44], an approach for visualizing a document's affective structure represented by a color-based navigation bar is detailed. Using affect analysis engine described in [42], sentences are annotated with six "basic" emotions [21], and then, the dynamics of affect throughout a text document is represented using color bar, in which colors used to symbolize each of these emotions are sequenced (Figure 1.4).


Figure 1.4 Visualizaton of affective structure of a text document using color bar [44]

The Aesthetiscope introduced in [43] was developed with the aim to generate color grids paired with inspiration texts (a word, a poem, or song lyrics). This program renders aesthetic impressions of text, such as thoughts, sensations, intuitions, and feelings, as a 16x9 grid of colors and emulates the creative process of a visual artist. Examples of color grids generated by the Aesthetiscope for the following texts (clockwise from upper-left corner): (1) the poem “Fire and Ice” by Robert Frost; (2) the poem “A Song of Despair” by Pablo Neruda; (3) the word ‘fear’; (4) the word ‘mourning’; (5) the word ‘god’; and (6) the word ‘envy’ – are shown in Figure 1.5.

Figure 1.5 Aesthetic renditions generated by the Aesthetiscope [43]

IN-SPIRE, a visual analytic tool designed to explore the emotional content of large collections of open domain documents, was introduced in [26]. Here, affect distribution for four concept pairs (positive - negative; virtue - vice; pleasure - pain; power cooperative - power conflict) is represented on a rose plot (see Figure 1.6) using different colors (the shades of the same color in pairs).

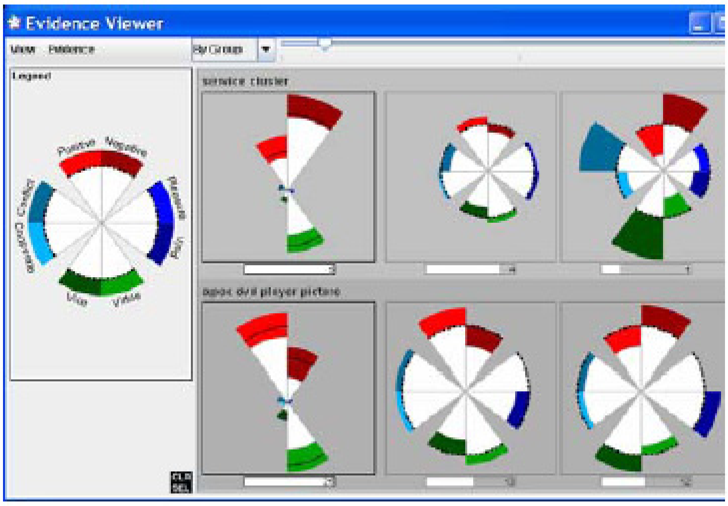



Figure 1.6 Affect representation on a color rose plot produced by IN-SPIRE [26]

Expressive and "dancing" text has been widely employed by researchers to accentuate affective information communicated through written language.

TextTone described in [35] aims at providing the means for unambiguously expressing emotion through text in online communication. In choosing a representation for emotion, users can control the text font-size, font-color, and font-face, and whether the text is bold, italicized, underlined or striked-through (see Figure 1.7). A kinetic typography technique focusing on changing the position, size, orientation, and representation of the words is used to convey emotion in text-based interpersonal conversations [39] and to automatically generate affective text animation [75]. For instance, in a work described in [75], authors annotated emotion categories with an appropriate kinetic behavior imitating human responses: joy – a sequence of hops; fear – palpitations; anger – strong tremble and blush (see Figure 1.8); surprise – sudden swelling; and sadness – deflation and squashing of text.

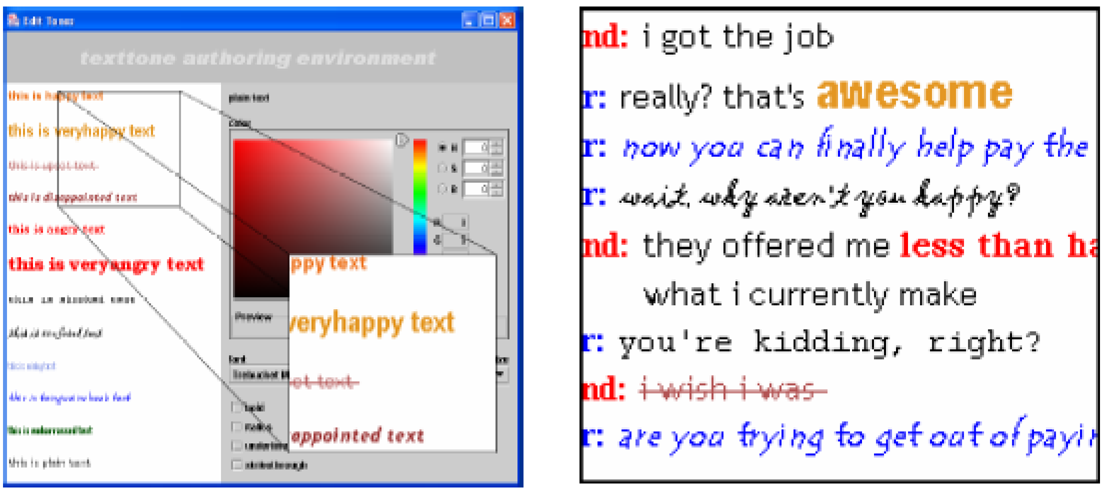



Figure 1.7 TextTone interface and an excerpt from archive of conversation [35]


Figure 1.8 Kinetic behavior of word "anger" [75]

To display affect in online conversations, EmpathyBuddy e-mail browser [42] uses black-and-white Chernov-style faces with rough features (see Figure 1.3 in the previous subsection). Still pictures of human faces with emotional expression [9] (see Figure 1.2 in the previous subsection) and animated three-dimensional computer graphics faces [22,54] were employed by researchers in order to reflect emotional states of users communicating in a chat environment. The screenshot of Virtual Messenger [22] interface with 3D avatar head is shown in Figure 1.9.

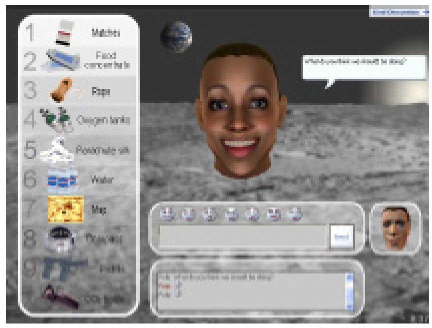


Figure 1.9 The Virtual Messenger Interface [22]

There exist variety of approaches to visual representation of affect communicated or sensed through text, and it is evident that their effectiveness greatly depends on the domain (e.g. poems, news, e-mails, blog posts, IM) in which these expressive tools are applied.

### 1.3.3 Proposed Approach to Textual Affect Recognition and Visual Representation

In this research, we address the tasks of recognition and interpretation of affect communicated through text messaging in virtual communication environments, specifically, in IM, where people tend to use an informal style of writing. The evolving nature of language in online conversations is a main issue in affect sensing from this media type, since sentence parsing might fail while syntactical structure analysis.

In order to facilitate sensitive and expressive communication in computer-mediated environments, we introduced a novel syntactical rule-based approach to affect recognition from text. The developed Affect Analysis Model was designed to handle not only grammatically and syntactically correct textual input, but also informal messages written in abbreviated or expressive manner. In contrast to machine-learning based approaches, for which detection of emotions on a sentence level still remains a challenge, the proposed rule-based approach processes each sentence in sequential stages, including symbolic cue processing, detection and transformation of abbreviations, sentence parsing, and word/phrase/sentence-level analyses. As the result, each analyzed sentence is automatically annotated with emotion (or neutral) label, numerical intensity, and communicative behavior (if identified).

The salient features of the proposed algorithm are:

1. analysis of nine emotions on the level of individual sentences;
2. the ability to handle the evolving language of online communications;
3. basis on database of affective words, interjections, emoticons, abbreviations and acronyms, modifiers;
4. vector representation of affective features of words, phrases, clauses and sentences;
5. consideration of syntactic relations and dependences between words in a sentence;
6. analysis of negation, modality, and conditionality;
7. consideration of relations between clauses in compound, complex, or complex-compound sentences;
8. emotion intensity estimation.

To make the user's experience in online communication enjoyable, exciting and fun, we have designed an IM system, AffectIM, and endowed it with the emotional intelligence by integrating with the Affect Analysis Model. We support the visual reflection of sensed affective states and nonverbal social behavior through use of the designed 2D cartoon-like avatars (graphical representations of users). Here, the effectiveness of visualization can be achieved with simplification and abstraction, which reduce the emotional expression to its essence. Also, a cartoon-like face allows us to exaggerate the expressive patterns.

The proposed system showed promising results on affect recognition and visualization in real examples of IM conversation, contributing thus to expressiveness of socially oriented online communications.

The remainder of the dissertation is structured as follows. Features of online conversation are discussed in Chapter 2. Chapter 3 describes the foundation for affective text classification. The developed Affect Analysis Model and design of expressive avatars are detailed in Chapter 4 and Chapter 5, respectively. Evaluation of the emotion sensing system and experimental results are discussed in Chapter 6. In Chapter 7, we describe the developed Instant Messaging application integrated with the Affect Analysis Model, and analyse the results of a user study. Finally, in Chapter 8, we discuss and conclude this work.

# Chapter 2

# Features of Online Communication

## 2.1 Peculiatities of IM Language

Many Internet users adopt online communications not only to conduct business but also to keep in touch with their family and friends, seek emotional support, or search for new interesting relationships.

Nowadays, IM has proven to be one of the most popular online applications. As stated by Shiu et al. [69], younger Internet users employ IM in greater number and more ardently than older generations. In contrast to chat rooms, which allow a group of people to type in messages that are seen by everyone in the room, IM systems provide communications in which only two individuals are involved. One of the crowded chat room problems is known as conversation congestion [51]. It is defined as a certain situation in which multiple topics are simultaneously running when many participants are synchronously involved in the same chat room. Hardly controllable flow of conversations in such situation results in preference of IM technology among users of online media. Some youth say they prefer IM to chatting because they feel it is easier to control conversational contacts and the flow of conversation itself [40].

In order to construct practically usable system, we investigated style of communication, linguistic and interactional features of real time online conversations.

Let us see a real example (annotated) of a chat conversation taken from the Yahoo! chat room “Music” (Table 2.1).

Table 2.1 Example of a chat conversation

| |
|---|
| **A**: *sorry if u* [you] *hear a bad song, just let me know and I'll stop it* |
| **B**: *no problem, hell I am just glad to see a real person for a change, lol* [laughing out loud]*, so many bots* |
| **A**: *I'll take that as a compliment ;) thnx* [thanks] |
| **B**: *yw* [you are welcome]*, lol, kinda to say too much without it soundy corny.* |
| **B**: *damn, I hate when I type too fast and leave out words* |
| **A**: *its not that, its because ur* [your] *brain is faster than ur fingers* |
| **A**: *its uncontrollable* |
| **A**: *at times* |
| **B**: *hmm, that could be true too* |
| **B**: *goodness, someone's bell is ringing, lol, hmm, nice to be popular eh* |
| **A**: *LOL* |
| **A**: *:-P* |
| **A**: *cant help it* |

When online, participants do not generally formulate long arguments. These would be considered as a monologue and, therefore, impolite because they bar the others from contributing and upset the conversational mode [5]. IM conversations are typed and often do not contain much, if any, punctuation because communication is informal [16]. As a result, conversations consist of short thoughts and phrases.

Davey et al. [16] state that the lexicon of IM terminology is in a state of constant flux. IM users have developed their own language where speed prevails over correct spelling, contributing thus to a greater interactivity. Authors have named this a "shorthand revolution" with such drawback as possible deterioration of today's Standard English. About 76% of the respondents reported using abbreviations in their IM conversations [16]. One aspect about abbreviations is the motivation behind them: "it is faster and requires less typing".

The main problem in messaging is the evolving language understanding by people and syntactical parsers. Although some of the abbreviations, such as ASAP ("as soon as possible"), FYI ("for your information"), or TIA ("thanks in advance"), are widely known, most of the abbreviations are only used within the context of IM. For example: BC ("because"), 2l8 ("too late"), CUL ("see you later"), etc. Often, participants have different levels of abbreviations in use, and find it annoying when they are used without surrounding context to help to perceive and correctly understand their meaning. Two problems, namely, understanding evolving language and determining intent from content, are discussed by Grinter and Eldridge in [27]. Researchers stated that "unlike e-mail, the language of text messaging is still evolving; consequently, it can be confusing". During their study, the teenagers reported using several different abbreviations for the same words, which makes text messages difficult to parse. For example, different messages shortened "tomorrow" to: "2moro", "2morra", "tomor", and

"2morrow". Concerning another problem, teenagers sometimes found it hard to figure out whether the message was serious or a joke, and consequently did not know how to react.

Below, we cite a few opinions regarding usage of abbreviations:

1. "*The whole point of internet chat abbreviation is speed, but instead of being faster, the conversation becomes unintelligible. It looks more like grunting. We've gone backwards in the evolution of conversation. We need a dictionary to see the list of possible meanings for each abbreviation. What I find most annoying is when people make abbreviations up with no surrounding context to help you understand, and when you ask them what it means, they change the subject*". (an answer to the question "Do you find Internet chat abbreviations annoying?", http://au.answers.yahoo.com)
2. "*I don't mind short ones like "g2g" or "lol". (I always thought that meant "lots of luck", but thats another story). I just hate when people use very long phrases like "TIARSPAYSNUTBIIHTU" that take a million years to figure out. (btw* [by the way]*, who can figure that out?)*" (excerpt from the archive of online forum on "most annoying internet chat phrases", http://forums.macrumors.com/archive/ )

Slobin [70] refers to "four basic ground rules which a communicative system must adhere to":

1. be clear;
2. be humanly processible in ongoing time;
3. be quick and easy;
4. be expressive.

We are proposing to resolve the problem in abbreviation understanding by communicating people by displaying meaningful transcriptions, in contrast colour or enclosed in brackets, along with original text, automatically. For instance, if original line is: "*bion, my new car is ftl. sfete*", message frame may display: "*bion* [believe it or not]*, my new car is ftl* [faster than light]. *sfete* [smiling from ear to ear]". In the case such system function is not necessary user could switch it off. Output of textual messages in clearly readable form might help people to avoid confusions, to learn and understand messages.

Since it is very important to consider abbreviations and their meanings while analysing text input, in our research the problem of correct processing of text by syntactical parser is settled by replacing abbreviations and acronyms by their proper transcriptions. In order to deal with the evolving language, we allow users to add new abbreviations and their meanings into database in the real time.

Successful computer-mediated communication, particularly within the IM environment, depends on the use of different symbolic conventions, such as emoticons (to portray emotion states or communicative behavior), capital letters or asterisks (to emphasize words), special symbols, etc. Trends show that IM users are increasingly turning to such expressive textual cues to supplement the lack of nonverbal (visual and aural) cues [18,29]. In her dissertation, Derks [18] examined the use of emoticons (short symbols that resemble facial displays) in text-based computer-mediated communication, and figured out that online messages are often imbued with emoticons to fill the conversational gaps and to give additional social and emotional meaning. Results of conducted study showed that:

1. the most common motives for emoticon use are "expressing emotion", "strengthening a message", and "expressing humour";
2. most emoticons are used towards friends compared to strangers;
3. more emoticons are used in positive than in negative contexts (spontaneously as well as intentionally).

## 2.2 Features of Diary-Like Blog Posts

We observed the collection of diary-like blog posts provided by BuzzMetrics [78]. Regarding examples of texts, we focused on online diary or personal blog entries that are typically written in a free style and are rich in emotional colorations. Two sample blog posts annotated by us and conveying 'joy' and 'sadness' emotions are shown in Table 2.2.

Table 2.2 Sample online diary entries

| | |
|---|---|
| joy | *heeheeeheeeee!* [laughing] *i have good news. I'm an aunt again! yippie* [interjection: an expression of excitement]*!! my sis* [sister] *gave birth to a boy today… i was hoping her to give birth tmr* [tomorrow] *loh* [loards of heavens]. *coz* [cause] *tmr's beckham's bday* [birthday]*!!! but anyways, yay* [interjection: an expression of happiness]! *hehh hehh. yippie yayy!! love the smell of babies.* |
| sadness | *…I'm still unhappy. I greeted this new job with open arms and a clear mind, tossing away every grain of discontent in my mind for the job I previously had. But still, I feel wrong: I don't feel my calling here, I'm not satisfied, I'm not fulfilled, I'm not proud. If anything, this job is becoming more and more of a nuisance to me…* |

Our observations suggest that every author practices a different style of writing. The most noticeable aspects of diary-like text are privacy, naturalism and honesty in the expression of the author's thoughts and feelings. We came to a conclusion that nature of such blog entries is very close to online IM conversations (with the evident difference in the size of messages, however), and decided to use sentences extracted from this collection [78] in our study because of difficulty to gather samples from real IM conversations.

# Chapter 3

# Foundation for Affective Text Classification

In this Chapter we focus on the basis of affective text classification as an important first task for the development of an automatic emotion recognition system.

## 3.1 Emotion and Communicative Function Categories

Why do people prefer to communicate and interact with a person who is expressive? In face-to-face communication, displayed emotions signal that the speaker is more sociable, open and humorous. All types of expressive means potentially carry significant communicative power and promote better understanding [2,12,63].

We believe that interaction in online conversations might benefit from the automation of multiple expressive channels, so that the user does not have to worry about visual self-presentation or misunderstandings as in standard IM systems, but can focus on the content of the conversation. Thus, we aim at recognizing and visualizing not only emotions in the text messages, but also communicative functions. Both can be "acted out" by the graphical avatars.

Since the purpose of affect recognition in an IM system is to relate text to avatar emotional expressions, affect categories should be confined to those that can be visually expressed and easily understood by users.

First, we investigated OCC model [56] that was created to model human emotions, and found out that it is cumbersome and too complex for using it as a basis for affect recognition in the system that visualizes communicated emotion. Twenty-two emotional categories need to be mapped to a possibly lower number of different emotional expressions. In [55], Ortony proposed simplified categorization with six positive ('joy', 'hope', 'relief', 'pride', 'gratitude', and 'love') and six negative ('distress', 'fear', 'disappointment', 'remorse', 'anger', and 'hate') categories. However, all positive OCC emotions share a single expression – smile. There are several different types of smiles, but their mapping to the positive OCC categories remains unclear.

We had analysed emotion categorizations proposed by theorists and listed in [57] (see Table 3.1 for details).

Table 3.1 A selection of lists of "basic" emotions (adapted from [57])

| Reference | Fundamental emotion | Basis for inclusion |
|---|---|---|
| Arnold | Anger, aversion, courage, dejection, desire, despair, fear, hate, hope, love, sadness | Relation to action tendencies |
| Ekman, Friesen, and Ellsworth | Anger, disgust, fear, joy, sadness, surprise | Universal facial expressions |
| Frijda | Desire, happiness, interest, surprise, wonder, sorrow | Forms of action readiness |
| Gray | Rage and terror, anxiety, joy | Hardwired |
| Izard | Anger, contempt, disgust, distress, fear, guilt, interest, joy, shame, surprise | Hardwired |
| James | Fear, grief, love, rage | Bodily involvement |
| McDougall | Anger, disgust, elation, fear, subjection, tender-emotion, wonder | Relation to instincts |
| Mowrer | Pain, pleasure | Unlearned emotional states |
| Oatley and Johnson-Laird | Anger, disgust, anxiety, happiness, sadness | Do not require propositional content |
| Panksepp | Expectancy, fear, rage, panic | Hardwired |
| Plutchik | Acceptance, anger, anticipation, disgust, joy, fear, sadness, surprise | Relation to adaptive biological processes |
| Tomkins | Anger, interest, contempt, disgust, distress, fear, joy, shame, surprise | Density of neural firing |
| Watson | Fear, love, rage | Hardwired |
| Weiner and Graham | Happiness, sadness | Attribution independent |

As the result of our investigation, for affect categorization we have decided to use the subset of emotional states defined by Izard [32]: 'anger', 'disgust', 'fear', 'guilt', 'interest', 'joy', 'sadness' ('distress'), 'shame', and 'surprise'.

Izard's theory [32] postulates the existence of discrete fundamental emotions with their motivational, phenomenological properties, and personal meanings. To support his theory, prominent psychologist presented series of original cross-cultural, developmental, and sociopsychological investigations of facial patterning, emotion recognition, and emotion labeling. According to Izard, there are two ways in which the fundamental emotions can be represented or operationally defined: (1) in facial behavior and (2) with concepts or verbal labels (via words). He proved that "each of the fundamental emotions, in its pure form, can be represented in a unique pattern of facial activity or facial behavior" and is "associated with a corresponding set of symbols or verbal labels". Additionally, Izard assumed that "the fundamental emotions are innate, universal phenomena", and evaluated this hypothesis in the light of cross-cultural research.

From the nine emotions mentioned, we can distinguish three types of affective states: (1) positive ('interest' and 'joy'); (2) negative ('anger', 'disgust', 'fear', 'guilt', 'sadness', and 'shame'); and (3) ambiguous ('surprise' depending on context). As Izard stated in [32]: "Phenomenologically, positive emotion has inherent characteristics which tend to enhance one's sense of well-being and to instigate and sustain approach toward, and constructive interactions or relations with, the involved persons, situations, or objects. Negative emotion tends to be sensed as noxious and difficult to tolerate and to investigate avoidance of and/or nonconstructive interactions or relations."

Besides specific or qualitatively distinct affective states, we defined several communicative functions that, we believe, can be derived from online conversations. We consider 'greeting', 'thanks', 'posing a question', 'congratulation', and 'farewell' as the basis for communicative behaviour identification.

## 3.2 Affect Database

### 3.2.1 Building the Lexical Source

In order to support the handling of abbreviated language and the interpretation of affective features of emoticons, abbreviations, and words, a special database was created using MySQL 5.0 [53].

The Affect database includes the following tables:

1. Emoticons
2. Abbreviations
3. Adjectives
4. Adverbs
5. Nouns
6. Verbs
7. Interjections
8. Modifiers
9. Words standing for communicative functions.

For accumulation of relevant and most often used emoticons and abbreviations, we employed five online dictionaries dedicated to and describing such data. Had been paying our attention to only those entries that occurred in at least three sources, we collected 364 emoticons, both of American and Japanese style (for example, ":">" and "=^_^=" for "blushing"), and the 337 most popular acronyms and abbreviations, both emotional and non-emotional (for example, "BL" for "belly laughing", "gj" for "good job", and "4U" – "for you").

Next category includes words conveying affective content. Persons use emotion words in particular contexts to negotiate aspects of social reality and to create that reality. Lutz argue in [46] that "in particular cultures and contexts, emotion words may be used to theorize about events, to moralize about or to judge them, and to advance one's interests by defining the situation in a particular way." From the source of affective lexicon, WordNet-Affect [74], we have taken 1627 words – adjectives (635), nouns (521), verbs (274), and adverbs (197) – that refer directly to emotions, mood, traits, cognitive states, behaviour, attitude, and sensations.

Moreover, we added 434 words that carry the potential to elicit affective states in humans to our database (for example, "beautiful", "disaster", "break", "deceive", "violate" etc.). These words are considered as indirect emotion words describing the objects and situations that lead to some emotional reactions. The reasoning is well depicted in the following words: "One obvious fact when we consider emotions is that certain sorts of objects or events tend to be systematically linked to a certain kind of emotion more than to others… As they develop and interact, organisms gain factual and emotional experience with different objects and situations in the environment and thus have an opportunity to associate many objects and situations which would have been emotionally neutral with the objects and situations that are naturally prescribed to cause emotions." [15].

Since interjections, such as "alas", "wow", "yay", "ouch", etc. are specific indicators of communicated emotion caused by unexpectedness, a long-awaited joyful event, or pain, they were collected as well. Further, we included 112 modifiers (e.g. "very", "extremely", "slightly", "hardly", "less", "not" etc.) into our database because they influence the strength of related words and phrases in a sentence.

In addition to affect-related words, we were taking into account words standing for communicative functions listed in the previous subsection.

### 3.2.2 Annotations of Database Entries

Emotion categories with intensities, or communicative function categories, were manually assigned to the entries of the database by three independent annotators (aged 25-35) studying at the Graduate School of Information Science and Technology, the University of Tokyo. Emotion intensity values range from 0.0 to 1.0, and describe the intensity degree of affective states from 'very weak' to 'very strong'. Annotators conformed to our guideline with the description of emotional state gradation within intensity levels (see Appendix A for details). For example, 'cheerful', 'glad', 'happy', 'joyful' and 'elated' all correspond to the 'joy' emotional state, but to a different degree of intensity.

#### 3.2.2.1 Annotations of Emoticons and Abbreviations

Emoticons and abbreviations were transcribed and related to named affective states (with intensity) or communicative functions, whereby each entry was assigned to only one category. The inter-rater agreement was calculated using Fleiss' Kappa statistics [23]. Fleiss' Kappa works for any number of rates giving categorical ratings to a fixed number of items. It can be interpreted as expressing the extent to which the observed amount of agreement among raters exceeds what would be expected if all raters made their ratings completely randomly. Shortly, Kappa gives a measure for how consistent the ratings are. The Kappa coefficient $k$ is defined as:

$$k = \frac{\overline{P} - \overline{P}e}{1 - \overline{P}e}, \tag{1}$$

where $\overline{P}$ is the relative observed agreement among raters; and $\overline{P}e$ is the probability that agreement is due to chance. The Kappa scoring ranges between 0 and 1, poor and complete agreement, respectively.

Statistical data on emoticons and abbreviations are brought together in Table 3.2. As seen from this data, the measured Kappa coefficients for emoticons and abbreviations are 0.94 and 0.93, respectively, showing strong annotation reliability.

Table 3.2 Statistical data on emoticons and abbreviations

| Parameter | Emoticons | Abbreviations |
|---|---|---|
| Total number | 364<br>(164 – American and 200 – Japanese style) | 337<br>(including 168 plain entries) |
| Number of labelled entries,<br>where:<br>1. Number of affect-related entries<br>2. Number of communicative-behavior-related entries | 364<br><br>308<br><br>56 | 169<br><br>89<br><br>80 |
| Number of raters | 3 | 3 |
| Number of labels | 14 | 14 |
| Fleiss' Kappa coefficient | 0.942 | 0.927 |
| Maximum acceptable intensity variance | 0.027 | 0.027 |
| Percentage of cases for resulting intensity correction, % | 7.79 | 6.74 |

The percentage distributions of emoticons and abbreviations according to resulting affective labels are shown in Figure 3.1 (a) and (b), respectively.

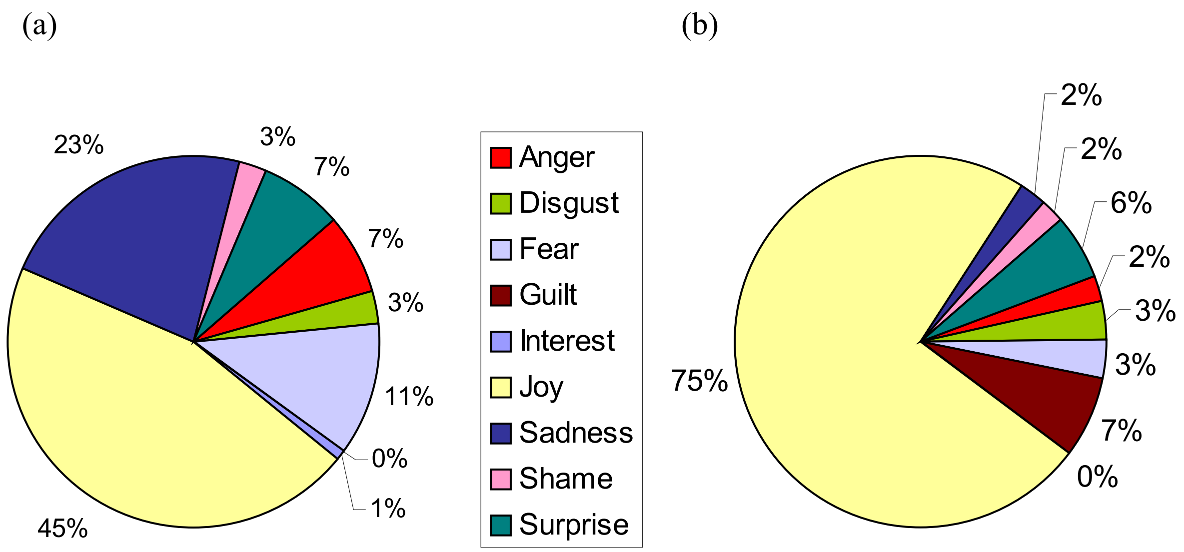



Figure 3.1 The percentage distributions of (a) emoticons and (b) abbreviations according to resulting affective labels

In the resulting intensity estimation for each affect-related entry, variance of data from the mean was taken into consideration. In statistics, the variance is considered as a measure of spread, that is how far the values deviate from the mean. The variance $\sigma^2$ of a set of values (in our case, intensity values given by three annotators) is defined as:

$$\sigma^2 = \frac{\sum (x - \bar{x})^2}{n}, \tag{2}$$

where $\bar{x}$ is the mean; $n$ is the number of data values ($n$=3); and $x$ stands for each data value in turn.

The maximum acceptable intensity variance (see Table 3.2) was measured using three values with step in 0.2 (e.g. 0.2, 0.4, and 0.6). If the variance was not exceeding a predetermined threshold, the resulting intensity was measured as the average of intensities given by three annotators. Otherwise, the intensity value responsible for exceeding the threshold was removed, and only the remaining values were taken into account.

Several examples of emoticons and abbreviations extracted from the developed database are listed in Table 3.3.

Table 3.3 Examples of emoticons and abbreviations extracted from Affect database

| Type | Symbolic representation | Meaning | Category | Intensity |
|---|---|---|---|---|
| Emoticons (American style) | :-) | happy | Joy | 0.6 |
| | :-o | surprise | Surprise | 0.8 |
| | :-S | worried | Fear | 0.4 |
| Emoticons (Japanese style) | \(^O^)/ | very excited | Joy | 1.0 |
| | (~_~) | grumpy | Anger | 0.3 |
| | m(._.)m | bowing, thanks | Thanks | - |
| Abbreviations | JK | just kidding | Joy | 0.3 |
| | 4gv | forgive | Guilt | 0.6 |
| | PPL | people | - | - |

### 3.2.2.2 Annotations of Affect-Related Words

Considering the fact that some affective words may express more than one emotional state, annotators could relate words to more than one category. For instance, in the annotation of the word “frustrated”, both ‘anger’ and ‘sadness’ emotions are involved, with intensities 0.2 and 0.7, respectively (Table 3.4).

Table 3.4 Examples of words taken from Affect database

| Affective word | Part of speech | Category | Intensity |
|---|---|---|---|
| cheerfulness | Noun | Joy | 0.3 |
| enthusiasm | Noun | Interest | 0.8 |
| | | Joy | 0.5 |
| astonished | Adjective | Surprise | 1.0 |
| frustrated | Adjective | Anger | 0.2 |
| | | Sadness | 0.7 |
| aggravated | Adjective | Anger | 0.5 |
| | | Disgust | 0.5 |
| | | Sadness | 0.3 |
| | | Fear | 0.1 |
| dislike | Verb | Disgust | 0.4 |
| discomfit | Verb | Anger | 0.1 |
| | | Sadness | 0.7 |
| | | Shame | 0.3 |
| remorsefully | Adverb | Guilt | 0.8 |
| | | Sadness | 0.5 |

Assignments of emotion labels to the same word might differ among annotators. We faced the difficulty of employing Fleiss’ Kappa coefficient [23] to measure inter-rater agreement here, because the important requirement of using it is that each entry needs to be assigned to only one of possible categories. For the resulting labeling, we only considered emotion categories that occurred in the assignments of at least two annotators. The most frequent emotion labels in resulting sets were 'joy' and 'sadness' (34.3% and 30.0% of overall number of affective words, respectively) whereas the least frequent was 'guilt' (3.1%). The percentage distribution of affective words with one, two, and three emotion labels is shown in Figure 3.2. Only one word (adjective "aggravated") was assigned with four resulting emotion labels (see Table 3.4).

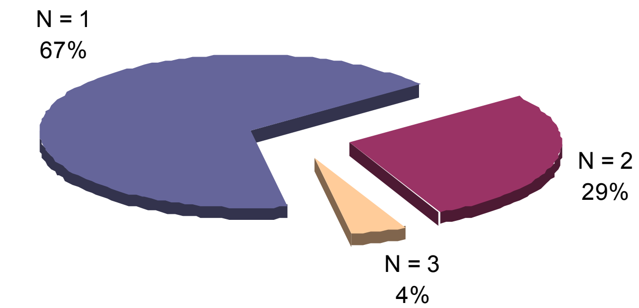



Figure 3.2 The percentage distributions of affective words with N emotion labels

Regarding the emotion intensity annotations of affective words, we observed interesting statistics within each of the nine emotion categories. Figure 3.3 shows the percentage of cases with valid variance of given intensities within each emotion category.

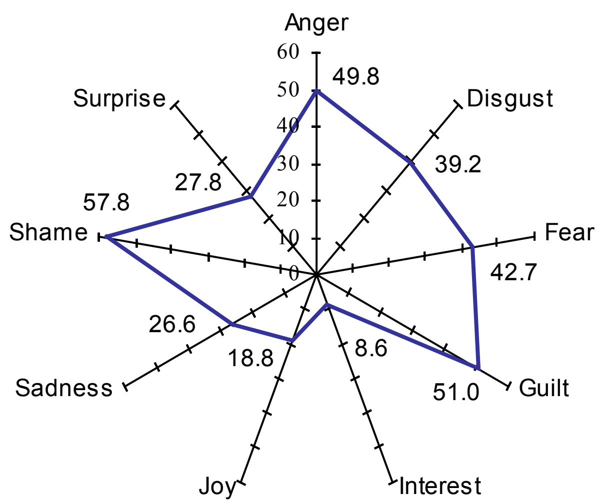



Figure 3.3 The percentage of cases with valid variance of intensities within each emotion category

As seen from the diagram, annotators easily agreed in intensity assignments to 'shame', 'guilt', and 'anger' categories, in contrast to frequent disagreement in cases of 'interest', 'joy', and 'sadness'. We can only speculate that disagreement is related to the huge diversity of 'joyful' and 'sad' synonymous words with different emotional colorations, and due to the fuzziness of the 'interest' concept (some of psychologists do not consider 'interest' as an emotional state at all).

Regarding indirect emotion words, about 300 nouns from WordNet-Affect [74] along with the categories, which they correspond to, were kindly provided by Alessandro Valitutti. Some examples are given in Table 3.5.

Table 3.5 Examples of indirect emotion nouns from WordNet-Affect and their annotations

| **Noun** | **Emotion categories from WordNet-Affect with annotations from Affect database** | **Resulting emotion labels and intensities defined automatically** |
|---|---|---|
| acceptance | Satisfaction – [Joy:0.3]<br>Gratitude – [Joy:0.6]<br>Liking – [Interest:0.3; Joy:0.5] | [Interest:0.3; Joy:0.6] |
| brave | Pride – [Joy:0.4]<br>Admiration – [Joy:0.6; Surprise:0.5] | [Joy:0.6; Surprise:0.5] |
| clash | Anger – [Anger:0.9]<br>Anxiety – [Fear:0.4]<br>Resentment – [Anger:0.6] | [Anger:0.9; Fear:0.4] |
| disapprobation | Blame – [Anger:0.1; Guilt:0.8; Sadness:0.4]<br>Distress – [Sadness:0.9]<br>Shame – [Shame:0.8]<br>Anger – [Anger:0.9] | [Anger:0.9; Guilt:0.8; Sadness:0.9; Shame:0.8] |
| promise | Hope – [Interest:0.1; Joy:0.3] | [Interest:0.1; Joy:0.3] |
| refusal | Sadness – [Sadness:0.9]<br>Anger – [Anger:0.9]<br>Resentment – [Anger:0.6]<br>Disappointment – [Sadness:1.0] | [Anger:0.9; Sadness:1.0] |
| well-being | Satisfaction – [Joy:0.3]<br>Joy – [Joy:0.9] | [Joy:0.9] |

Since Affect database had already included direct emotion words (annotated by three persons) representing emotion categories of WordNet-Affect, we considered their emotion labels and intensities (see middle column of Table 3.5) while defining emotion states and intensities, which indirect emotion words relate to. Therefore, these indirect emotion nouns were annotated automatically (see some results in the last column of Table 3.5). The maximum intensity level within the same emotion label was taken as a resulting intensity for that emotion state.

#### 3.2.2.3 Assignments of Coefficients to Modifiers

In the sentences, adverbs of degree have an impact on neighbouring verbs, adjectives, or another adverb, and are used to mark that the extent or degree is either greater or less than usual [7]. In [6], authors use adverbs of degree to modify the score of adjectives in sentiment analysis. In our work, such adverbs along with some of prepositions constitute the set of modifiers. Two annotators gave coefficients for intensity degree strengthening or weakening (from 0.0 to 2.0) to them, and the result was averaged (see Table 3.6).

Table 3.6 Examples of modifiers with coefficients of intensity degree strengthening or weakening

| Modifier | Category, coefficient range | Coefficient |
|---|---|---|
| certainly | adverb of affirmation, from 1.0 to 2.0 | 1.2 |
| perfectly | | 1.9 |
| arguably | adverb of doubt, from 0.0 to 1.0 | 0.5 |
| relatively | | 0.8 |
| immensely | strong intensifying adverb, from 1.0 to 2.0 | 1.8 |
| significantly | | 2.0 |
| adequately | weak intensifying adverb, from 0.0 to 1.0 | 0.9 |
| slightly | | 0.2 |
| hardly | negation, 0.0 | 0.0 |
| never | | 0.0 |

# Chapter 4

# The Developed Affect Analysis Model

We developed an algorithm for analysis of affect expressed by text messages. The proposed algorithm consists of five main stages:

1. symbolic cue analysis;
2. syntactical structure analysis;
3. word-level analysis;
4. phrase-level analysis;
5. sentence-level analysis.

For the realization of this algorithm we employed Java programming tools. The working flow of the Affect Analysis Model is presented in Figure 4.1.

## 4.1 Symbolic Cue Analysis

In the *first stage*, the sentence is tested for occurrences of emoticons, abbreviations, acronyms, interjections, "?" and "!" marks, repeated punctuation and capital letters.

First of all, punctuation marks of a sentence are delimited from words in order to disambiguate sentence punctuation marks from those belonging to emoticons. The sensed "!" mark, repeated punctuation and capital letters are considered as an emphasis of the communicated emotion.

If there is an emoticon or abbreviation related to an emotional state, no further analysis of affect in text is performed based on the simplifying assumption that the emoticon (or abbreviation) dominates the affective meaning of the entire (simple or compound) sentence. It is known that people type emoticons and emotional abbreviations to show actual feeling (e.g. "*I have taken the exams timetable already :S* [worry; 'fear:0.4']"), or to avoid misleading the other participants, for instance, after irony, joke, or sarcasm (e.g. "*Thank you so much for your kind* *encouragement :-(* [‘sadness:0.8’]” or “*If you miss the meeting, I will hunt you down and murder you :)* [‘joy:06’]”). In a face-to-face communication sarcasm is conveyed by a positive tone or a smile and a negative message or the opposite [62]. Similarly, emoticons “can create ambiguity and express sarcasm online by varying the valence of the emoticon and the valence of the message” [18].

On the other hand, if there are multiple emoticons or emotion-relevant abbreviations in the sentence, we determine the prevailing (or dominant) emotion based on the following two (tentative) rules:

1. when emotion categories of the detected emoticons (or abbreviations) are the same (e.g. “*G* [grin; ‘joy:0.6’] *it is nice song too ;-)* [winking; ‘joy:0.3’]”), the higher intensity value is taken for this emotion;
2. when they are different (e.g. “*I did not save that song :S* [worry; ‘fear:0.4’], *please send it once more ;”>* [blushing; ‘shame:0.5’]”), the category (and intensity) of the emoticon occurring last is dominant.

Regarding the visualisation by the avatar, when both emotional state and communicative function category appear in a sentence, for example, “*I’ll take that as a compliment ;) thnx*”, two animations (‘joy’ with intensity 0.3 and ‘thanks’) will be sequentially displayed.

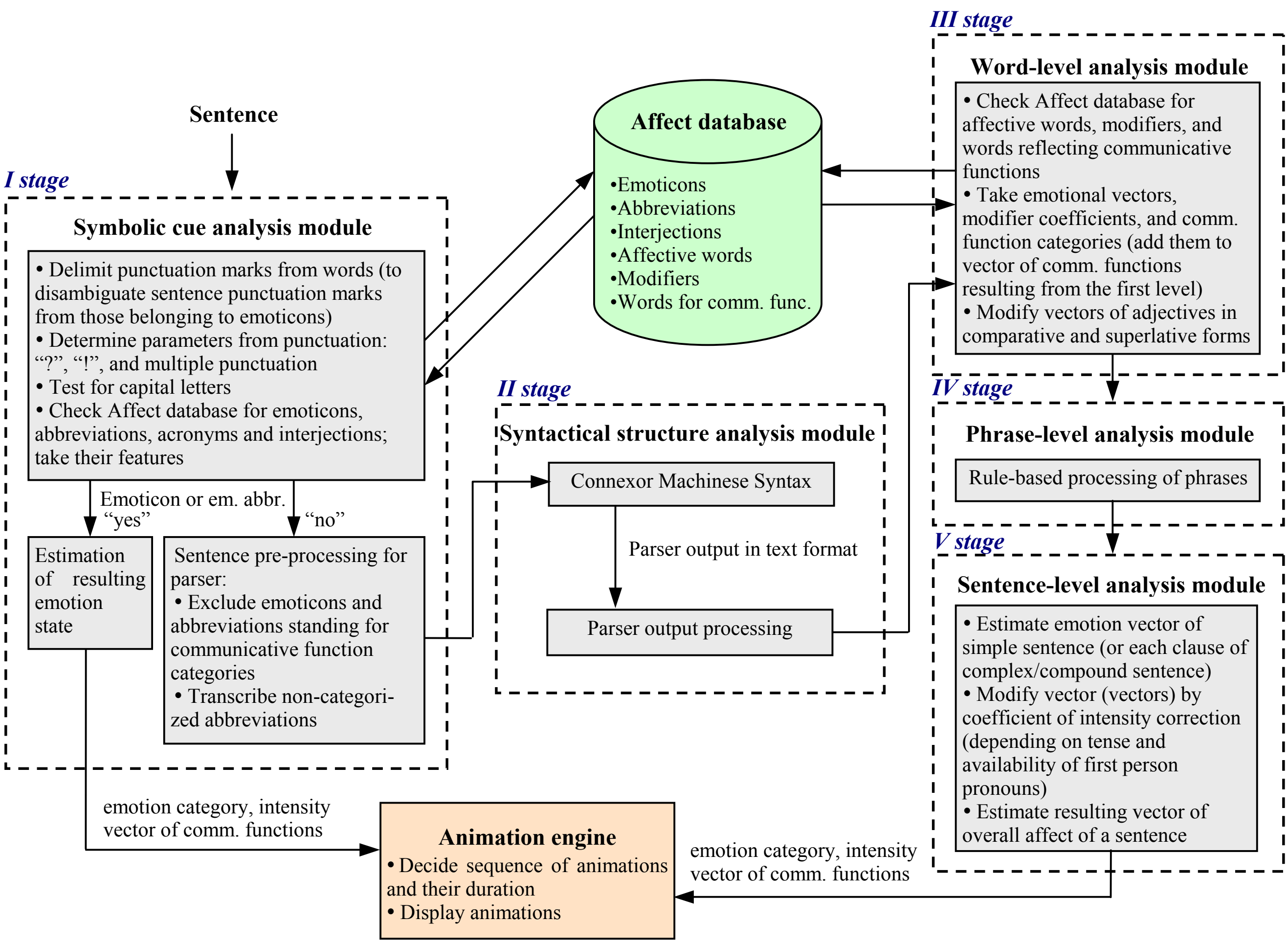



Figure 4.1 Working flow of the Affect Analysis Model

As interjections are added to text to reflect an author's feelings, like in the sentences "*Oh no, I forgot that the exam was today!*" and "*But anyways, yay!*", they are analysed as well.

In case of an interrogative sentence, we process it further at subsequent stages in order to identify whether the question expresses strong emotion or not. While some researchers ignore such sentences at all, we believe that questions, like "*Why do you irritate me so greatly?*" may carry emotional content.

If there are no emotion-relevant emoticons or abbreviations in a sentence, we prepare the sentence for parser processing: emoticons and abbreviations standing for communicative function categories are excluded from the sentence; and non-emotional abbreviations and acronyms are replaced by their proper transcriptions found in the database (e.g. "*I m* [am] *stressed bc* [because] *i have frequent headaches*"). In such a way, the problem of correct processing of abbreviated text by syntactical parser is settled.

## 4.2 Syntactical Structure Analysis

The *second stage* is devoted to syntactical structure analysis, and it is divided into two main subtasks:

1. sentence analysis by syntactical parser, Connexor Machinese Syntax [13];
2. parser output processing.

Connexor Machinese Syntax [13] provides a full analysis of texts by showing how words and concepts relate to each other in sentences, with very competitive speed and accuracy. This tool assigns to text its meaning-oriented syntactic structure, helping thus analytic applications understand text beyond the level of words, phrases and entities.

The used parser returns exhaustive information for analysed sentences, including word base forms (lemmas), parts of speech, dependency functions representing relational information between words in sentences, syntactic function tags, and morphological tags. An example of Connexor Machinese Syntax output for the sentence "*Despite his endless demonstrations of rude power, brotherly love always prevails*" is shown in Table 4.1.

Table 4.1 An example of Connexor Machinese Syntax parser output

| Token id | Text | Lemma | Syntactic relations and dependencies | Syntax and morphology |
|---|---|---|---|---|
| 1 | Despite | despite | cla:>12 | @ADVL %EH PREP |
| 2 | his | he | attr:>3 | @A> %>N PRON PERS GEN SG3 |
| 3 | endless | endless | attr:>4 | @A> %>N A ABS |
| 4 | demonstrations | demonstration | pcomp:>1 | @<P %NH N NOM PL |
| 5 | of | of | mod:>4 | @<NOM-OF %N< PREP |
| 6 | rude | rude | attr:>7 | @A> %>N A ABS |
| 7 | power | power | pcomp:>5 | @<P %NH N NOM SG |
| 8 | , | , | | |
| 9 | brotherly | brotherly | attr:>10 | @A> %>N A ABS |
| 10 | love | love | subj:>12 | @SUBJ %NH N NOM SG |
| 11 | always | always | frq:>12 | @ADVL %EH ADV |
| 12 | prevails | prevail | main:>0 | @+FMAINV %VA V PRES SG3 |
| 13 | . | . | | |
| 14 | <p> | <p> | | |

From the parser output, we can read off the syntactic and morphologic characteristics of each token, the relations between words in a sentence, and dependences between clauses. While handling the parser output, we represent the sentence as a set of primitive clauses (either independent or dependent). Each clause might include Subject formation, Verb formation and Object formation, each of which may consist of main element (subject, verb, or object) and its attributives and complements.

The developed algorithm can detect not only subjects represented by noun phrases, but also subjects represented by gerund (non-finite verb form) like in the sentence "*Walking on the beach is pleasure*", by an infinitive like in the sentence "*To offend the youngest child is obscene action*", or by a full clause, introduced by "that", itself containing a subject and a predicate like in the sentence "*That tomorrow weather will be sunny is great*".

For the processing of complex or compound sentences, we build so called "relation matrix", which contains information about dependences that the verbs belonging to different clauses have.

## 4.3 Word-Level Analysis

After handling the result from the previous analysis stage, the system transfers the data to the *third stage*, word-level analysis. For each word in the database we built, either the communicative function category is taken as a feature or the affective features of a word are represented as a vector of emotional state intensities e = [anger, disgust, fear, guilt, interest, joy, sadness, shame, surprise]. For example, e("rude")=[0.2,0.4,0,0,0,0,0,0,0]; e("brotherly")=[0,0,0,0,0,0.2,0,0,0]; and e("love")=[0,0,0,0,0.8,1.0,0,0,0]. In the case of a modifier, the system identifies its coefficient (e.g. coeff("barely")=0.4).

Adjectives and adverbs often have two forms that indicate degrees of comparison:

1. comparative form;
2. superlative form.

The comparative form, which is made by adding "-er" or a preceding "more" to the positive form, either shows a greater degree than the positive form or makes a comparison between two persons or things. The superlative form, which is made by adding "-est" or a preceding "most" to the positive form, indicates the greatest degree of a quality or quantity among three or more persons or things.

Since the developed Affect database contains words only in their dictionary form, one important system function at this stage is to increase the intensity of the emotional vector of an adjective (e.g. "glad"), or emotional adverb, if it is in comparative or superlative form (e.g. "gladder", "gladdest"), by multiplication on values 1.2 or 1.4, respectively.

For example:

e("glad")=[0,0,0,0,0,0.4,0,0,0];
e("gladder")=[0,0,0,0,0,0.48,0,0,0];
e("gladdest")=[0,0,0,0,0,0.56,0,0,0].

## 4.4 Phrase-Level Analysis

In the *fourth stage*, phrase-level analysis is performed. The purpose of this stage is to detect emotions involved in phrases, and then in Subject, Verb, and Object formations. Words in a sentence are interrelated and, hence, each of them can influence the overall meaning and affective bias of a statement.

We have defined general types of phrases, and rules for processing them with regard to affective content:

1. adjective phrase: modify the vector of adjective (e.g. e("extremely doleful") = coeff("extremely") * e("doleful") = 2.0 * [0,0,0,0,0,0,0.4,0,0] = [0,0,0,0,0,0,0.8,0,0]);
2. noun phrase: output vector with the maximum intensity within each corresponding emotional state in analysing vectors (for instance, e1=[0..0.7..] and e2=[0.3..0.5..] yield e3=[0.3..0.7..], e.g. e("brotherly love")=[0,0,0,0,0.8,1.0,0,0,0]);
3. verb plus adverbial phrase: output vector with the maximum intensity within each corresponding emotional state in analysing vectors (e.g. e("shamefully deceive")=[0,0.4,0,0,0,0,0.5,0.7,0] where e("shamefully")=[0,0,0,0,0,0,0,0.7,0] and e("deceive")= [0,0.4,0,0,0,0,0.5,0,0]);
4. verb plus noun phrase: if verb and noun phrase have opposite valences (e.g. "break favourite vase", "enjoy bad weather"), consider vector of verb as dominant; if valences are the same (e.g. "like honey", "hate crying"), output vector with maximum intensity in corresponding emotional states;
5. verb plus adjective phrase (e.g. "is very kind", "feel bad"): output vector of adjective phrase.

The rules for modifiers are as follows:

1. adverbs of degree multiply or decrease emotional intensity values;
2. negation modifiers such as "no", "not", "never", "any", "nothing" and connector "neither…nor" cancel (set to zero) vectors of the related words, i.e. "neutralize the emotional content" (e.g. "*Yesterday I went to a party, but nothing exciting happened there*"). We think that negation constructions do not reverse emotional meaning of words from positive to negative or vice versa. As an example, "not splendid" is not necessarily reverse of "splendid".
3. prepositions such as "without", "except", "against", "despite" cancel vectors of related words (for example, statement "*despite his endless demonstrations of rude power*" and sentence "*I climbed the mountain without fear*" are neutralized due to prepositions).

Statements with prefixed words like "think", "believe", "sure", "know", "doubt" or with modal operators such as "can", "may", "must", "need", "would" etc. are not considered by our system because they express a modal attitude towards the proposition. Conditional clause phrases beginning with "after", "although", "as if", "as though", "before", "even if", "even though", "if", "if only", "unless", "whether", "when", "whenever", etc. are disregarded as well (e.g. "*I eat when I'm angry, sad, bored…*", or "*If only my brain was like a thumbdrive, how splendid it would be*").

There might be several emotional vectors within each of the Subject, Verb, or Object formations. During this stage, we apply the described rules to phrases detected within formation boundaries. Finally, each formation can be represented as a unified vector encoding its emotional content.

## 4.5 Sentence-Level Analysis

In the *fifth and final stage*, the overall emotion of a sentence and its resulting intensity degree are estimated. The developed algorithm enables processing of different types of sentences, such as: simple, compound, complex (with complement or relative clauses), or complex-compound.

### 4.5.1 Emotional Vector of a Simple Sentence (or of a Clause)

The emotional vector of a simple sentence (or of a clause) is generated from Subject, Verb, and Object formation (SF, VF, and OF, respectively) vectors resulting from phrase-level analysis.

The main idea here is to first derive emotion vector of Verb-Object formation relation. It is estimated based on the "verb plus noun phrase" rule described above. In order to apply this rule, we automatically determine valences of Verb and Object formations using their unified emotion vectors (particularly, non-zero-intensity emotion categories).

The estimation of the emotion vector of a clause (Subject plus Verb-Object formations) is then performed in the following manner:

1. if valences of Subject formation and Verb formation are opposite (e.g. Subject formation = "my darling", Verb formation = "smashed", Object formation "his guitar"; or Subject formation = "troubled period", Verb formation = "luckily comes to an end"), we consider the vector of the Verb-Object formation relation as dominant;
2. otherwise, we output the vector with maximum intensities in corresponding emotional states of vectors of Subject and Verb-Object formations.

Let us consider the processing of Subject formations themselves containing Verb-Object formation (for example, "*to offend the youngest child*" in "*To offend the youngest child is obscene action*") or a full clause, Subject plus Verb-Object formations (for example, "*tomorrow weather will be sunny*" in "*That tomorrow weather will be sunny is great*"). In such cases, first, we estimate emotional vector of main Subject formation, formed by Verb-Object formation or an embedded clause, using rules described above. And then, we estimate the resulting emotional vector of a whole sentence.

It is important to note that the developed system enables the differentiation of the strength of the resulting emotion depending on the tense of a sentence and availability of first person pronouns. We introduce this idea based on psychological literature. Consideration of tense is very important because "emotions typically occur in response to an event, usually a social event,

**real**, **remembered**, **anticipated**, or **imagined**" [21] (emphasis added by authors). As Ekman states, "sometimes when people give an account of an emotional experience they unexpectedly begin to re-experience the emotion" [21]. "Genuine" emotion expressions display that emotion is now felt, whereas so-called "referential" expressions occur most often when people talk about past or future emotional experiences. Therefore, we assume that the strength of emotions conveyed by text depends on tense.

As to first person pronouns, people tend to use them to "more directly portray the speaker as the experiencer of the emotion" [45], and to underline the strength of an emotion. Many researchers neglect these phenomena. They ignore the difference between "*I am charmed by cherry flowers of Japan*" vs. "*Cherry flowers of Japan are charming*" (we think that emotion conveyed through first sentence is stronger than in case of second one), and some of them completely disregard sentences in past or future tense and without first person pronouns.

According to our proposal, the emotional vector of a simple sentence (or of a clause) is multiplied by the corresponding empirically determined coefficient of intensity correction (Table 4.2).

Table 4.2 Coefficients of intensity correction

| **Tense** | **First person pronouns (FPP)** | |
|---|---|---|
| | yes | no |
| present | 1 ("*My vase is broken*") | 0.8 ("*She is annoying*") |
| past | 0.8 ("*He made me angry*") | 0.4 ("*It was the most joyous feeling*") |
| future | 0.4 ("*I will enjoy the trip to Egypt*") | 0 ("*The game will definitely bring them triumph*") |

The dominant emotion of the sentence is determined according to emotion state with the highest intensity within emotional vector. However, if there are several emotion states with the same maximum intensity in the resulting vector, we use the function that selects the prevailing emotion randomly.

Let us consider the example of processing of the following simple sentence: "*My darling smashed his most favourite guitar without regret*" (Figure 4.2, where emotion vector e = [anger, disgust, fear, guilt, interest, joy, sadness, shame, surprise]; SF, VF, and OF mean Subject, Verb, and Object formations, respectively; the superscripts $^{0}$, $^{-}$, and $^{+}$ indicate 'neutral', 'negative', and 'positive' valences, correspondingly).

| | word: | word-level: | phrase-level: | |
|---|---|---|---|---|
| **SF:** | my | $e^0$ = [0,0,0,0,0,0,0,0,0] | $e^+$ = [0,0,0,0,0,0.7,0,0,0] | |
| | darling | $e^+$ = [0,0,0,0,0,0.7,0,0,0] | | |
| **VF:** | smashed | $e^-$ = [0,0,0.6,0,0,0,0.8,0,0] | $e^-$ = [0,0,0.6,0,0,0,0.8,0,0] | $e^-$ = [0,0,0.6,0,0,0,0.8,0,0] |
| | without | modif. coeff=0.0 | $e^0$ = [0,0,0,0,0,0,0,0,0] | |
| | regret | $e^-$ = [0,0,0,0.2,0,0,0.1,0,0] | | |
| **OF:** | his | $e^0$ = [0,0,0,0,0,0,0,0,0] | $e^0$ = [0,0,0,0,0,0,0,0,0] | $e^+$ = [0,0,0,0,0,0.84,0,0,0] |
| | most | modif. coeff = 1.4 | $e^+$ = [0,0,0,0,0,0.84,0,0,0] | |
| | favourite | $e^+$ = [0,0,0,0,0,0.6,0,0,0] | | |
| | guitar | $e^0$ = [0,0,0,0,0,0,0,0,0] | $e^0$ = [0,0,0,0,0,0,0,0,0] | |

| sentence-level: | |
|---|---|
| 1. | ($SF^+$ and $VF^-$) yields domination of (VF and OF); |
| 2. | ($VF^-$ and $OF^+$) yields domination of VF; |
| 3. | e (sentence) = e ($VF^-$) = [0,0,0.6,0,0,0,0.8,0,0]; |
| 4. | e (sentence) * coeff (tense:‘past’; FPP:‘yes’) = [0,0,0.6,0,0,0,0.8,0,0] * 0.8 = [0,0,0.48,0,0,0,0.64,0,0] |
| 5. | result (“My darling smashed his favourite guitar without regret”): ‘sadness:0.64’. |

Figure 4.2 Example of affect sensing in a simple sentence

### 4.5.2 Emotional Vector of a Compound Sentence

A compound sentence is composed of at least two independent clauses, but no dependent clauses. The clauses are joined by a comma and coordinate connector, or a semicolon with no conjunction.

In order to estimate emotional vector of a compound sentence, first of all we evaluate emotional vectors of independent clauses that compound it.

Then, we define the resulting vector of compound sentence based on the following rules:

1. with comma and coordinate connectors “and” and “so” (e.g. “*It is my fault, and I am worrying about consequences*”, “*Exotic birds in the park were amazing, so we took nice pictures*”), or with a semicolon with no conjunction: output the vector with the maximum intensity within each corresponding emotional state in the resulting vectors of both clauses;
2. with coordinate connector “but” (e.g. “*They attacked, but we luckily got away!*”): the resulting vector of a clause following after the connector is dominant.

### 4.5.3 Emotional Vector of a Complex Sentence

A complex sentence is a sentence with an independent clause and at least one dependent (embedded or subordinating) clause. The dependent clause is introduced by either a subordinate conjunction (see commonly used conjunctions in Table 4.3) or a relative pronoun such as "who" or "which". Some subordinating conjunctions, when used to introduce a phrase instead of a full clause, become prepositions with identical meanings.

Table 4.3 Common subordinating conjunctions

| **Subordinating conjunctions** | | | | |
|---|---|---|---|---|
| after | because | in order that | than | when |
| although | before | now that | that | whenever |
| as | even if | once | though | where |
| as if | even though | rather than | till | whereas |
| as long as | if | since | unless | wherever |
| as though | if only | so that | until | while |

In the Section 4.4 we mentioned that in the developed Affect Analysis Model conditional clause phrases beginning with "after", "although", "as if", "as though", "before", "even if", "even though", "if", "if only", "unless", "whether", "when", "whenever", etc. are neutralized due to these subordinate conjunctions. Therefore, emotional vector of dependent clause starting with one of the above listed conjunctions represents zero vector, and the vector of independent clause forms the resulting emotional vector of such complex sentence.

If subordinating clause in the complex sentence is connected with independent clause through conjunctions like "as", "because", "since", for the estimation of resulting vector of such complex sentence we take the maximum intensity within each corresponding emotional state in the resulting vectors of both clauses.

We can distinguish two types of embedded clauses:

1. Complement clauses.
2. Relative clauses.

#### 4.5.3.1 Sentences with Complement Clauses

Special subordinating conjunctions, so called complementizers (e.g. "whether", "that" etc.), introduce complement clauses (for example, "*I wonder whether we will go to amusement park next weekend*" and "*We hope that you feel comfortable*").

There are basically three complementizers in English language: "that", "for-to" ("for" precedes the complement sentence and the "to" precedes the auxilliary constituent of the complement sentence), and what is known as "POSS-ing" ("POSS" means the possessive suffix, which is affixed to the noun, and the "-ing" means the suffix attached to a verb stem) [11]. There are some examples listed:

1. with "that": Sam preferred *that* John take the blame.
2. with "for-to": Sam preferred *for* John *to* take the blame.
3. with "POSS-ing": Sam preferred John*'s taking* the blame. John resented Sam*'s telling* the truth.

In order to process the sentence with complement clause, first we derive the emotional vector of a complement clause (e.g., "*John take the blame*", "*John to take the blame*", "*John's taking the blame*" or "*Sam's telling the truth*"), then create Object formation for the main clause using this vector, and finally estimate resulting emotional vector of main clause with added Object formation. Shortly, we represent such sentence as a simple one, using the following pattern: 'who-subject does-verb what-object', where object is represented as a complement clause.

#### 4.5.3.2 Sentences with Relative Clauses

Our program is also able to handle complex sentences containing adjective (relative) clauses introduced by "who", "whom", "whose", "that", "which", and "where". An adjective clause is a dependent clause that modifies a noun. Depending on the role (subject or object) that relative pronoun plays in the embedded clause, sentences are called subject relatives (see examples 1 and 2 below) or object relatives (see example 3) [11].

The followings are examples of complex sentences with relative claauses:

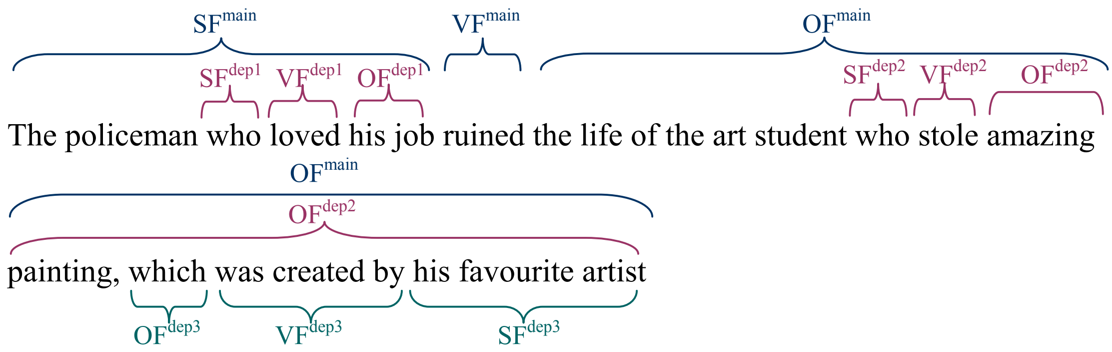
1. The wolf *who ate the grandmother* scared Little Red Riding Hood.
2. The wolf *who ate the grandmother who lived in the cottage* scared Little Red Riding Hood. (a case of multiple embedding)
3. The wolf *who the woodman killed* scared Little Red Riding Hood.

In our algorithm, the sentences of such kind are analyzed in the following manner:

1. emotional vector of adjective clause is estimated;
2. then, this emotional vector is added to the Subject or Object formation of the main clause depending on the role of word, which the adjective clause relates to. For example, in a sentence "*The man who loved the woman robbed the bank*" adjective clause "*who loved the woman*" relates to the subject "*man*"; and in a sentence "*The man robbed the bank where his loved wife was working*" adjective clause "*where his loved wife was working*" relates to the object "*bank*";
3. emotional vector of whole sentence is estimated.

Figure 4.3 represents the example of processing of the following complex sentence with multiple embedding of relative clauses: "*The policeman who loved his job ruined the life of the art student who stole amazing painting, which was created by his favourite artist*".

In Figure 4.3, emotion vector e = [anger, disgust, fear, guilt, interest, joy, sadness, shame, surprise]; SF, VF, and OF represent Subject, Verb, and Object formations, respectively; the superscripts $^{0}$, $^{-}$, and $^{+}$ indicate 'neutral', 'negative', and 'positive' valences, correspondingly; $^{main}$ and $^{dep}$ mean belonging to 'main' and 'dependent' clauses, respectively.




**processing:**

1. Emotion vectors of relative clauses, that do not have dependent clauses, are estimated and added to the corresponding Subject or Object Formations:
   1) $e^{dep1}$ ("who loved his job") = $e^{dep1}$ ($SF^{0dep1}$ & $VF^{+dep1}$ & $OF^{0dep1}$) = coeff (tense:'past'; FPP:'no')$^*$ * * [0,0,0,0,0.8,0.9,0,0,0] = [0,0,0,0,0.32,0.36,0,0,0] = $e^{+dep1}$;
   $SF^{main}$ = "the policeman" & $e^{+dep1}$ = [0,0,0,0,0.32,0.36,0,0,0] = $SF^{+main}$;
   2) $e^{dep3}$ ("which was created by his favourite artist") = $e^{dep3}$ ($SF^{+dep3}$ & $VF^{0dep3}$ & $OF^{0dep3}$) = = coeff (tense:'past'; FPP:'no')$^*$ * [0,0,0,0,0,0.6,0,0,0] = [0,0,0,0,0,0.24,0,0,0] = $e^{+dep3}$;
   $OF^{dep2}$ = "amazing painting" & $e^{+dep3}$ = [0,0,0,0,0,0.4,0,0,1] & [0,0,0,0,0,0.24,0,0,0] yield [0,0,0,0,0,0.4,0,0,1] = $OF^{+dep2}$;
2. Then, described analysis procedure continues recursively till resulting emotion vector estimation:
   3) $e^{dep2}$ ("who stole amazing painting, which was created by his favorite artist") = $e^{dep2}$ ($SF^{0dep2}$ & $VF^{-dep2}$ & $OF^{+dep2}$) = coeff (tense:'past'; FPP:'no')$^*$ * ([0,0.2,0,0,0,0,0.5,0,0] & [0,0,0,0,0,0.4,0,0,1] yield [0,0.2,0,0,0,0,0.5,0,0]) = [0,0.08,0,0,0,0,0.2,0,0] = $e^{-dep2}$;
   $OF^{main}$ = "the life of the art student" & $e^{-dep2}$ = [0,0.08,0,0,0,0,0.2,0,0] = $OF^{-main}$;
   4) $e^{main}$ ("the policeman who loved his job ruined the life of the art student who stole amazing painting, which was created by his favourite artist") = $e^{main}$ ($SF^{+main}$ & $VF^{-main}$ & $OF^{-main}$) = coeff (tense:'past'; FPP:'no')$^*$ * ([0,0,0,0,0.32,0.36,0,0,0] & [0,0,0,7,0,0,0,0.9,0,0] & [0,0.08,0,0,0,0,0.2,0,0] yield [0,0.08,0.7,0,0,0,0.9,0,0])= = [0,0.03,0.28,0,0,0,0.36,0,0] = $e^{-main}$;
   5) result (sentence): 'sadness:0.36'.

$^*$coeff (tense:'past'; FPP:'no') = 0.4 (see Table 4.2)

Figure 4.3 Example of affect sensing in a complex sentence with multiple embedding of relative clauses

## 4.5.4 Emotional Vector of a Complex-Compound Sentence

Sentences with at least two independent clauses and one or more dependent clauses are referred to as complex-compound sentences (for example, "*Max broke the china cup, which Mary was awarded for the best song with, so he regretted profoundly*"). While processing such type of sentences, first we generate emotional vectors of dependent clauses, then – of complex sentences, and finally, we analyse compound sentence formed by independent clauses.

After the dominant emotion of the analysed sentence is determined, the relevant parameters are sent to the animation engine.

# Chapter 5

# Design of Expressive Avatars for Visualization of Affect and Nonverbal Behavior

"*All emotions use the body as their theater…*"
Antonio Damasio

In this Chapter, we propose to endow a graphical representation of a user in Instant Messaging, an avatar, with the ability to express emotions and to play social nonverbal behavior, on the basis of textual affect sensing and interpretation of communicative functions conveyed by online conversations.

Using Adobe Photoshop 7.0 developed by [1], we had designed two 2D animated avatars (see Figure 5.1) that can represent one's identity in an IM community. Animations of avatar expressive patterns are driven by the output of the developed Affect Analysis Model.

## 5.1 Personality

Experience of feeling and expression of emotions are greatly influenced by the personality type of a person and individual differences. In our work, we consider one personality trait, extraversion, to differentiate ways and strength of avatar expressiveness. Extraverts are characterized by frequent and exaggerated expression of emotions and enthusiasm. By contrast, introverts tend to be quiet and prefer to hide their emotions.

In order to differentiate the level of emotional expressiveness, we animated our avatars according to personality type.

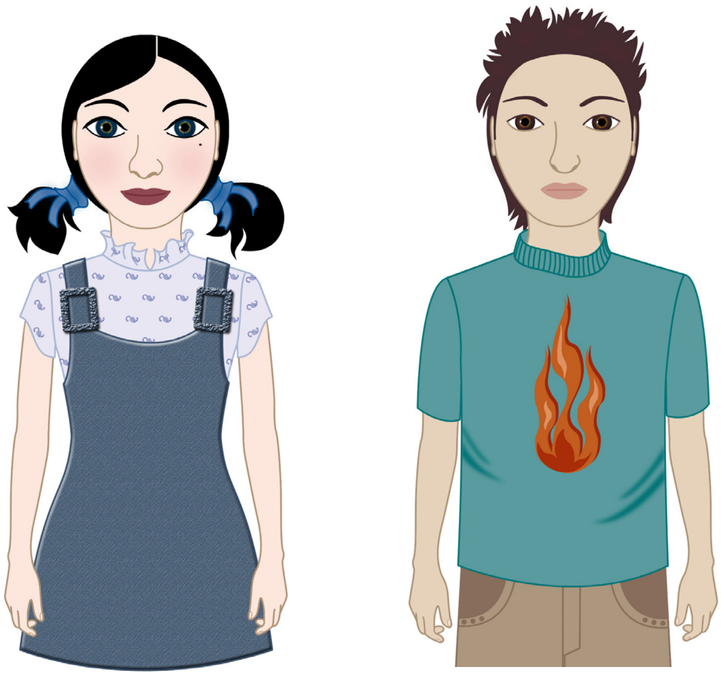


Figure 5.1 Designed 2D cartoon-like avatars, female and male

## 5.2 Emotions

> "*Stated briefly, how something is expressed may carry more significance and weight than what is said, the words themselves. Accompanied by a smile or a frown, said with a loud, scolding voice or a gentle, easy one, the contents of our communications are framed by our holistic perceptions of their context*"
>
> Adam Blatner

In order to enable the avatar to display emotions of different intensity degrees, animations were created according to low, middle, and high level of emotion intensity. For example, 'cheerful', 'happy', and 'elated' all correspond to the 'joy' emotional state, but to a different degree of intensity (see Appendix A for details). Table 5.1 summarizes some main characteristic features of expressive means in relation to communicated emotion.

Table 5.1 Emotional states and relevant expressive means (data partially taken from [32])

| **Emotion** | **Expressive means** | |
|---|---|---|
| **anger** | eyebrows | frown; drawn together and down, causing vertical wrinkles beween |
| | eyes | opened wide, fixated; may become reddened; stare gaze; pupils contracted |
| | mouth | ajar mouth; teeth usually clenched tightly; rigidity of lips and jaw; lips may be tightly compressed, or may be drawn back to expose teeth |
| | nose | nostrils distended |
| | neck | muscles strained and rigid |
| | hands | clenched fists; hands are set against sides or on hips |
| | body | stiffness of posture |
| **disgust** | eyebrows | eyebrows slightly pulled down |
| | eyes | narrowed eyes; may be partially closed as result of nose being drawn upward |
| | mouth | upper lip drawn up; pressed lips; corners drawn down and back; tongue moved forward, may be slightly protruding |
| | nose | wrinkled; drawn up |
| | head | turned to the side quasi avoiding something |
| | hands | in front of the body quasi pushing the source of disgust away |
| **fear** | forehead | wrinkled transversely |
| | eyebrows | raised |
| | eyes | widely open; staring; pupils dilated |
| | mouth | open and rigid; crooked lips; corners drawn back and depressed |
| | cheeks | lower parts drawn down and back, due to action of mouth |
| | nose | nostrils flared |
| | chin | trembling |
| | hands | in front of the body quasi pushing the source of fear away |
| **guilt** | forehead | may be wrinkled vertically or transversely |
| | eyebrows | inner corners may be drawn down |
| | eyes | downcast or glancing gaze |
| | mouth | lips drawn in; corners depressed; lower lip may either protrude slightly, or be tucked between teeth; sigh |
| | head | lowered |
| | hands | haggard shoulders; hands are behind back |

Table 5.1 (continuation)

| **Emotion** | **Expressive means** | |
|---|---|---|
| **interest** | eyebrows | slightly lifted or slightly lowered |
| | eyes | may be exaggeratedly opened and fixed; lower eyelids may be raised as though to sharpen visual focus; increased pupil size; sparkling gaze |
| | mouth | slightly smiling; lips may be parted; underjaw may be dropped slightly |
| | head | head is slightly inclined to the side |
| **joy** | eyebrows | slightly lowered; forehead relatively smooth |
| | eyes | 'smiling'; bright; partially closed (more exaggerated in laughing); wrinkles formed in outer corners |
| | mouth | genuinely smiling; corners lifted; in smiling may be closed or slightly opened; in laughter, corners pulled back and up; teeth show; upper lip is tense; nasolabial grooves appear |
| | cheeks | raised, pushing up lower eyelid, making face seem shorter and broader |
| | nose | may appear to elongate and taper; nose wrinkles may appear |
| **sadness** | eyebrows and forehead | muscles contracted, pulling eyebrows together; inner corners may be raised or lowered slightly; vertical wrinkles appear between inner corners |
| | eyes | eyelids contracted; eyes are partially closed; moisture in eyes |
| | mouth | corners drawn in; downturning mouth; tense; center of lower lip pushed upward; furrow from nose to mouth formed |
| | hands | haggard shoulders |
| **shame** | eyebrows | 'sheepish' movement of eyebrows |
| | eyes | downcast or glancing gaze |
| | mouth | tense lips |
| | cheeks | blushing |
| | head | lowered |
| **surprise** | forehead | muscles horizontally contracted, creating transverse wrinkles |
| | eyebrows | slightly raised (with open eyes) or lowered |
| | eyes | either wide open and rounded or blinking |
| | mouth | opened by the jaw drop, or rounded to form an "O"; the lips are relaxed |
| | jaw | slack; muscles of lower face elongated |
| | hands | moved apart |

As examples, nine emotional states expressed through facial expressions and gestures of the female avatar designed by us are shown in Figure 5.2.


Figure 5.2 Examples of emotional facial expressions and gestures displayed by female avatar

## 5.3 Communicative Behavior

The richness of the information cues is a salient aspect of effective interpersonal communication. This also holds true within the virtual environment context.

Based on their automatic identification from text, our avatar can act out the five communicative functions listed in Section 3.1. They can be displayed in sequence with emotional animations. However, the communicative function 'posing a question' (ask for confirmation, ask for information, ask for something, or posing a rhetorical question) is an exceptional case:

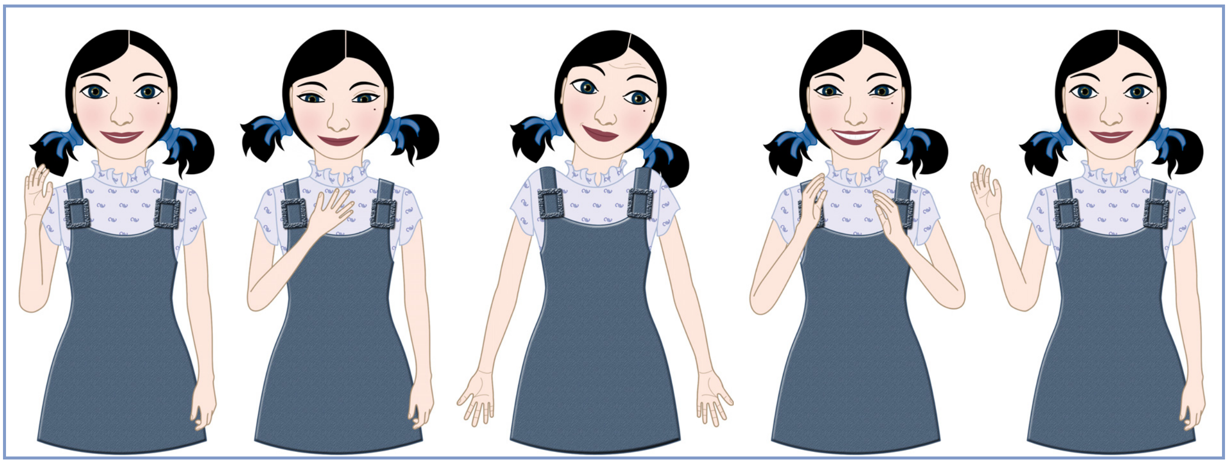
1. in case the interrogative sentence carries strong affect (like in the sentence "*Why does this have to be so hard?*"), an emotional animation is displayed;
2. on the other hand, communicative behavior accompanying 'posing a question' is performed if conveyed affect has low or middle level of intensity (e.g. "*Where did we go wrong?*").

Each of the five communicative functions has an associated specific lexicon and nonverbal behavior. Some examples are listed in Table 5.2.

Table 5.2 Communicative functions, relevant lexicon, and expressive means

| **Communicative function** | **Relevant lexicon and symbols** | **Expressive means** |
|---|---|---|
| greeting | hi; hello; rehi [hi, again]; wb [welcome back]; (^o^)/ [hi] | smile; cheery waving in salutation |
| thanks | thank; grateful; tia [thanks in advance]; m(._.)m [bowing, thanks] | gratifying smile; bowing; palms are crossed on the heart |
| posing a question | 'wh' question expressions; how; ruok [are you ok]; :-/ [confused]; ? | quizzical gaze directed at the user; raised eyebrows; head is tilted forward a bit; raised shoulders |
| congratulation | congratulation; praiseworthy; gj [good job]; llta [lots, lots of thunderous applause]; d=(^o^)=b [thumbs up] | admiring gaze; smile; clap of hands |
| farewell | bye-bye; goodbye; cyo [see you online]; tfs [three finger salute (ctrl-alt-del)]; (-_-)/~ [bye-bye] | farewell waving |

The examples of communicative behavior acted out by female avatar are shown in Figure 5.3.



greeting thanks posing a question congratulation farewell

Figure 5.3 Examples of communicative behavior acted out by female avatar

The animations of our avatar also include idle movements so as to provide a sense of liveliness: eye blinks; changing of gaze direction to avoid “dull stare”; yawning; slight head and body movements; playing with fingers; smoothing hair; rubbing nose; touching earlobe; hands behind head; folding arms; hands on hips.

By introducing the animated avatars, we strive to provide vivid and expressive visual signals to enhance socially oriented online communication media.

# Chapter 6

# Evaluation of Affect Analysis Model

## 6.1 Test Application

For evaluation purposes, we implemented a test interface with an avatar based on the Affect Analysis Model (see Figure 6.1). The application was realized using Java programming language.

The developed interface consists of three frames:

1. Text Input;
2. Output of Affect Analysis Model;
3. Visualization.


Figure 6.1 Test application of Affect Analysis Model

The sentences for affect recognition are typed in the field of Text Input. The input might include one sentence or a whole paragraph, which then is divided into single sentences by our program while preparation for analysis. Each sentence is processed by the Affect Analysis Model, the results of which (emotion and intensity, communicative functions, if any) are displayed in the field of Output of Affect Analysis Model. The Visualization frame shows the animated female avatar that performs emotional and communicative behavior according to the results of affect recognition.

## 6.2 Experimental Setup

For the system evaluation, we collected 160 sentences from a corpus of online diary-like blog posts provided by [78].

Three independent annotators labeled the sentences with one of nine emotion categories discussed in Section 3.1 (or neutral) and a corresponding intensity value. Additionally, they were asked to identify communicative functions conveyed by text. The annotations from human raters are considered as "gold standard" for the evaluation of algorithm performance.

We ran the same set of sentences on the developed test application integrated with Affect Analysis Model. The sentences annotated by human raters and analyzed by our algorithm are listed in the Appendix B along with the annotations.

## 6.3 Discussions of Obtained Results

The reliability of human raters' annotations was measured using Fleiss' Kappa coefficient. The level of agreement is moderate (0.58), and suggests that persons' comprehension, interpretation and evaluation of emotions are individual and might depend on personality type and emotional experience. As Davitz [17] stated: "In some respects, the experiences of each subject are undoubtedly unique. In fact, for any one person, even though experiences at different times are labeled by the same [emotional] term, these experiences are likely to differ somewhat from one another."

When comparing system results with the "gold standard", we found that the percentage of cases where the dominant emotion category obtained by our algorithm matches with at least one of three raters' annotation is 79.4% (from which 84.3% are categorized as emotional, and 15.7% - neutral) of all sentences. In view of the variety of considered emotions (9 categories and neutral), the accuracy of our system seems reasonably high. In 70%, system output agrees with at least two annotators.

Regarding the cases when the Affect Analysis Model resulted in neutral emotion, the output of our system agreed with at least one human out of three annotators in 59% of cases.

We also evaluated the system performance with regard to intensity estimation. The percentage of emotional sentences according to the measured distance between intensities given by human raters (averaged values) and those obtained by Affect Analysis Model is shown in

Table 6.1. As seen in the table, our system achieved satisfactory results for emotion intensity estimation.

Table 6.1 Percentage of emotional sentences according to the range of intensity difference between human annotations and output of algorithm

| **Range of intensity difference** | [0.0 – 0.2] | (0.2 – 0.4] | (0.4 – 0.6] | (0.6 – 0.8] | (0.8 – 1.0) |
|---|---|---|---|---|---|
| **Percentage of sentences, %** | 68.2 | 26.2 | 4.7 | 0.9 | 0.0 |

The evaluation of the Affect Analysis Model algorithm showed promising results regarding its capability to recognize affective information in text from an existing corpus of informal online communication.

On the other hand, the system strongly depends on the created source of lexicon, Affect database. This limits its performance if indirectly emotion-related words occur in analyzed sentence (e.g. "*Oh yes, not forgetting, they had a mini chocolate fountain!*"). Furthermore, the Affect Analysis Model does not yet disambiguate word meanings (e.g. word "kill" is typically associated with negative emotions, but the phrase "to kill the audience" conveys 'surprise') and it fails to process expression-modifiers such as "to no end", "to death" (e.g. "*I love my ipod to death*"), etc.

We also encountered the problem of annotating sentences in isolation, i.e, without context. For example, the sentence "*There are no other terms that could really put me in a better position*" was rated as 'sad' by two annotators, as 'joy' by one, and as 'neutral' by our system, whereas originally it belongs to a 'sad' monologue. Therefore, when analyzing text messages in IM, we should also take into account the emotion dynamics throughout the conversation, or its "overall mood".

# Chapter 7

# Instant Messaging Application Integrated with the Affect Analysis Model

We developed Instant Messaging system, AffectIM, endowed with emotional intelligence. For the realization of web-based application, we used Java Server Pages (JSP) and Apache Tomcat server [4]. The developed application includes 15 JSP pages, 9 servlets, and Java files from the Affect Analysis Model. Database supporting AffectIM system was created using MySQL 5.0 [53].

## 7.1 Development of AffectIM Database

The logical structure of AffectIM database containing data about users and their conversations is represented in Figure 7.1. The database consists of 6 tables:

1. ‘users’. This table collects personal information about each registered AffectIM user: first and last names; sex; ID and password for login to the system; key to the control question and answer for the verification of forgotten password; personality type (either ‘extrovert’ or ‘introvert’); and avatar ID.
2. ‘friends’. This table gathers data about relations between users, where ‘relation_id’ marks two friends.
3. ‘im_status’. The user online status is represented in this table, where ‘status_online’ is either ‘in’ (available for online conversations) or ‘out’ (nonavailable) and ‘im_time’ shows the exact time of changing the status in the pattern ‘yyyy-mm-dd hh:mm:ss’.
4. ‘messages’. All conversations between ‘friends’ are archived in this table. Each message has its own ID and is marked by ‘relation_id’, ‘sender’ (AffectIM ID of sender) and exact time of sending in the pattern ‘yyyy-mm-dd hh:mm:ss’. The

additional information, particularly: transcribed message (with transcriptions of abbreviated text in brackets, and with <stop> indicators between sentences); emotion with intensity (or neutral) and communicative functions of each sentence in the message, – is provided by the Affect Analysis Model.

5. ‘questions’. In this table, control questions (e.g., “*What is your pet’s name?*”, “*What is your favourite color*”, “*How do you like spending holidays?*”, etc.) aimed at verification of forgotten AffectIM password are listed.
6. ‘avatars’. The complement information about visual representation of a user, avatar, is saved in this table.

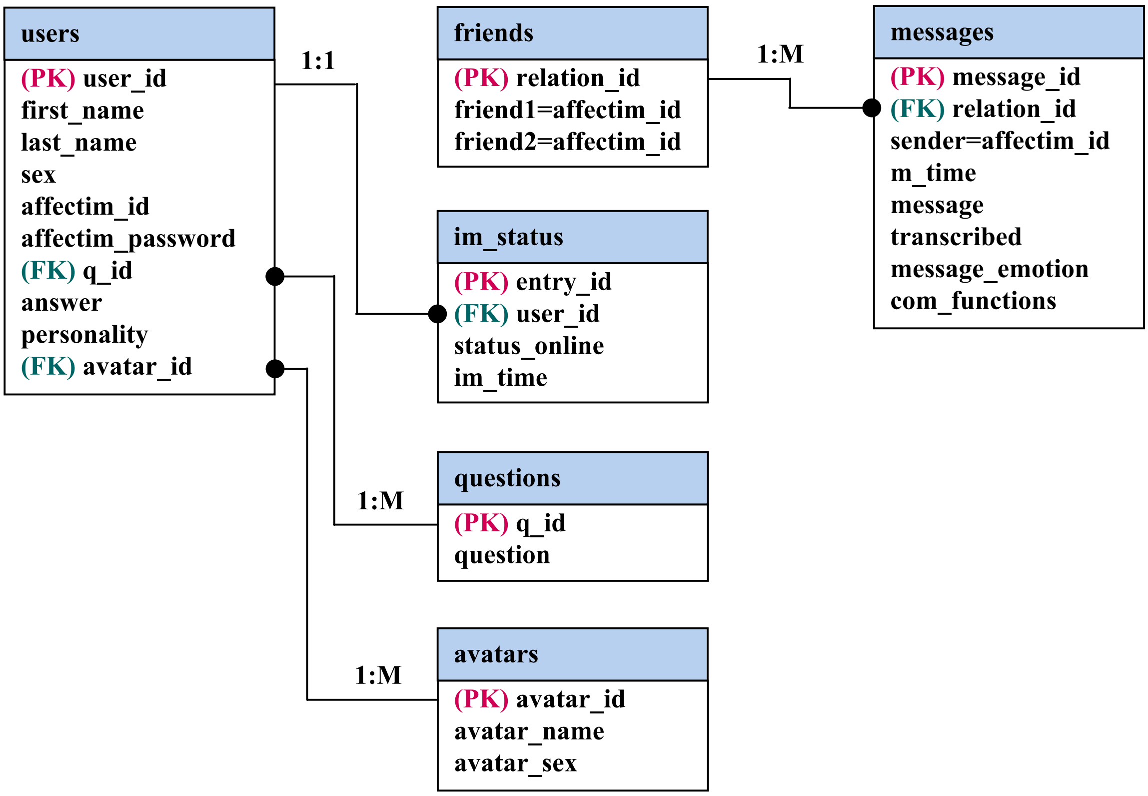



Figure 7.1 Logical structure of AffectIM database

The relations between tables of the developed AffectIM database are as follows: “1:1” (“one to one”) is between ‘users’ and ‘im_status’; and “1:M” (“one to many”) is between table pairs ‘friends’-‘messages’, ‘questions’-‘users’, and ‘avatars’-‘users’.

## 7.2 System Architecture and User Interface

The AffectIM system was developed as a web-based application running through the Internet browser, so that the user does not need to download and install the system on local computer. The system architecture is schematically represented in Figure 7.2.

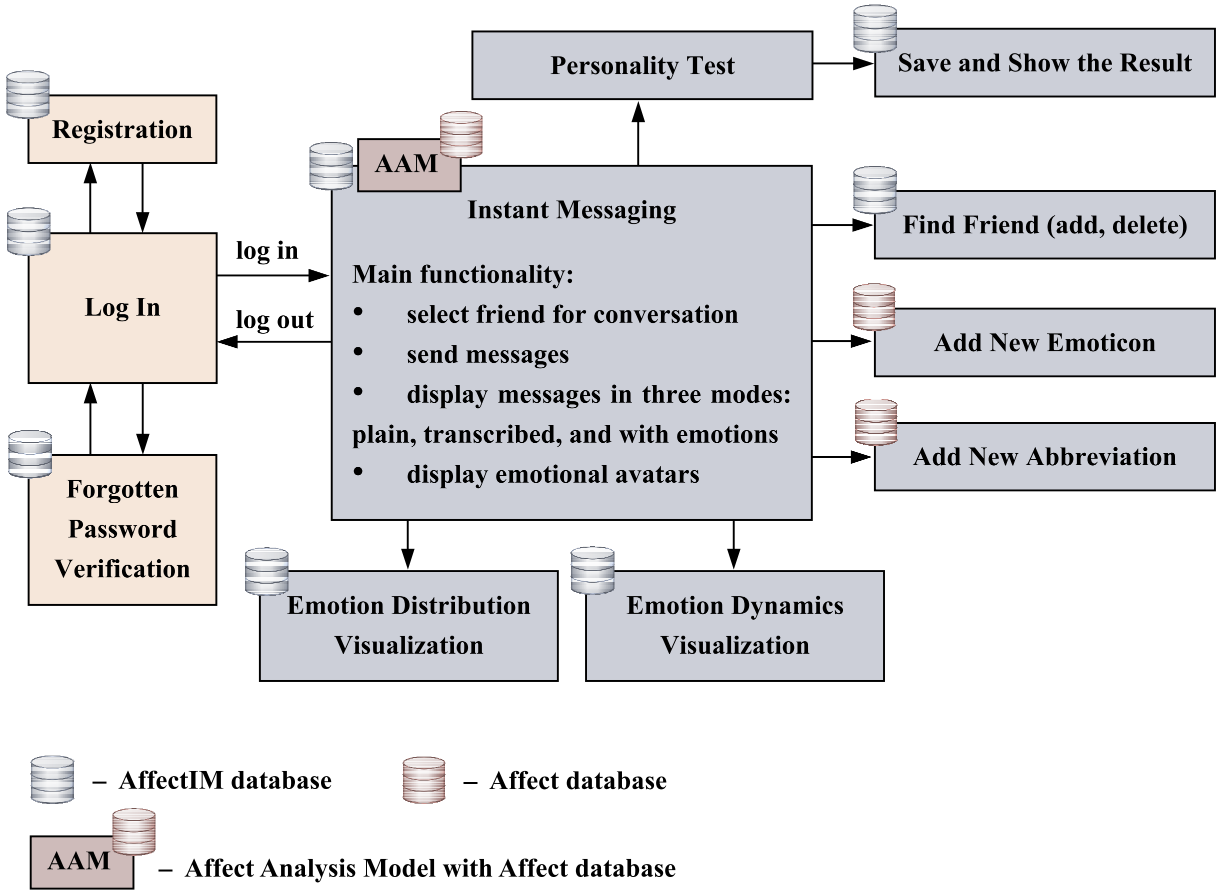



Figure 7.2 Architecture of AffectIM system

The interface was designed to be user-friendly and attractive. The 'welcome' page (Figure 7.3) invites user to log in to the system using AffectIM ID and password, to register and get AffectIM ID (for newbie), or to verify forgotten password.

During the registration stage (Figure 7.4), user fills the personal information in, decides the desired AffectIM ID and password for log in to the system, and answers the control question. The system verifies either AffectIM database had already included this AffectIM ID or not, and then reject or confirm the registration.

If on the stage of log in to the system user realizes that he/she had forgotten the registration password, the application will provide the possibility to extract it from the database using control question and user's answer given earlier during registration stage (Figure 7.5).


Figure 7.3 'Welcome' page of AffectIM

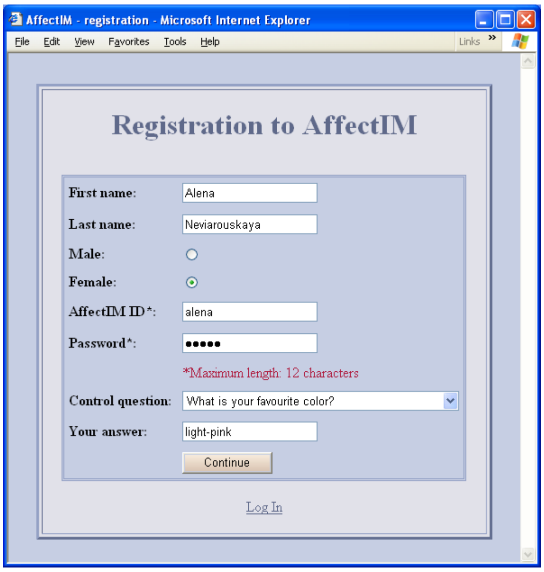



Figure 7.4 ‘Registration’ page of AffectIM


Figure 7.5 ‘Password verification’ page of AffectIM

When logged in, user has the opportunity to create contacts with existing AffectIM users, or to delete the relations with them (Figure 7.6).

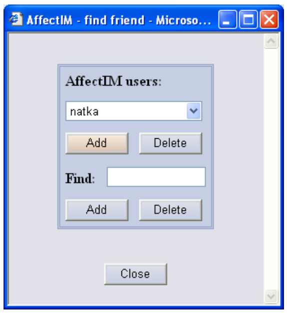



Figure 7.6 ‘Find friend’ page of AffectIM

Since we had designed only two avatars, the graphical representative is automatically selected by the system according to the user’s sex. Initially, the personality type of a user is set to ‘introvert’ by default. In order to fit the level of avatar expressiveness to the personality type of a user, he or she is invited to select the personality characteristic along an extroversion-introversion scale manually, or to pass a short personality test regarding extraversion (see Figure 7.7). The questionnaire includes 15 questions, the answers to which are considered as a basis for the resulting decision (either ‘extrovert’ or ‘introvert’).

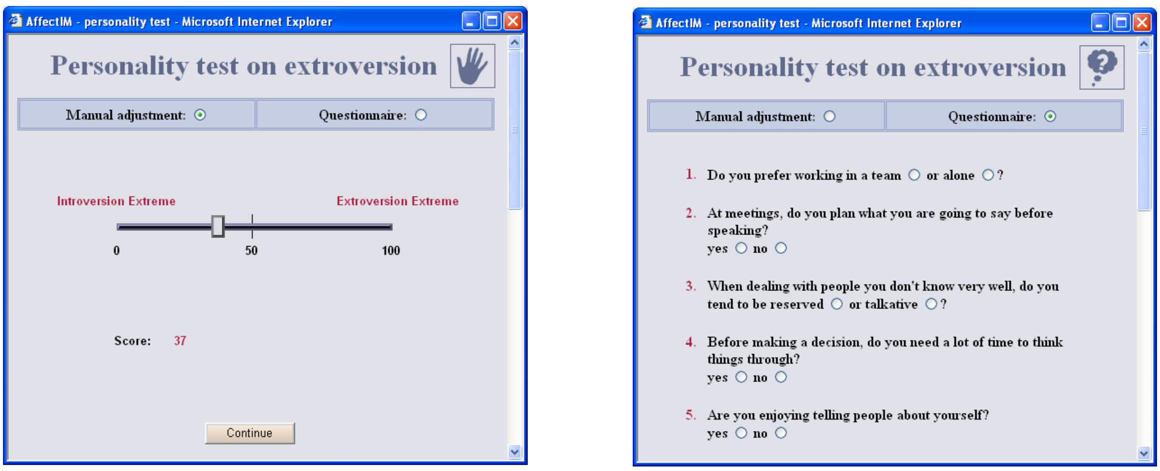



Figure 7.7 ‘Personality test’ pages of AffectIM: manual adjustment and questionnaire

The main window of the AffectIM system while online conversation is shown in Figure 7.8.

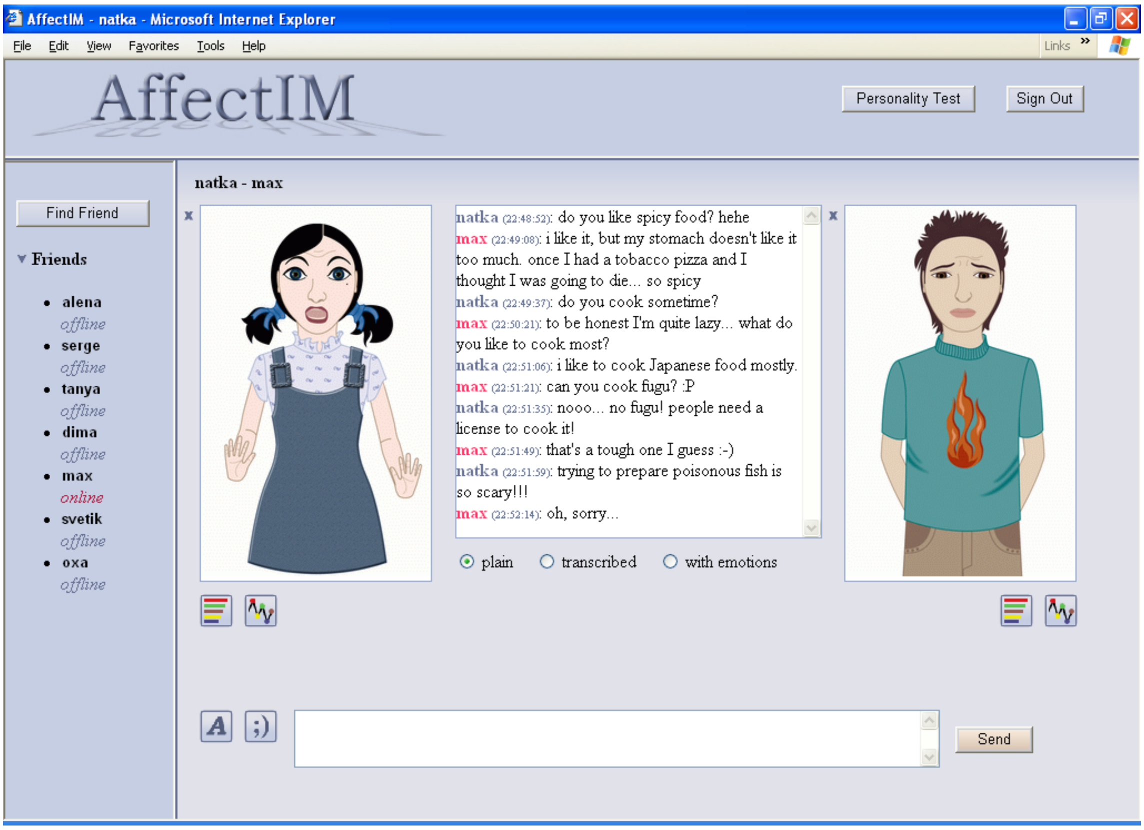



Figure 7.8 'Instant Messaging' page of AffectIM

From the list of friends displayed in the left frame, user selects the person (available online), whom he wishes to have the conversation with. The central frame allows user to type and send the messages; displays the conversation flow in three modes: plain, transcribed, and with emotions; and displays emotional avatars (own – to the left of conversation field, and friend's – to the right). Two buttons located under the avatar image are responsible for visualization of emotion distribution (Figure 7.9) and emotion dynamics (Figure 7.10) in the messages of this person.

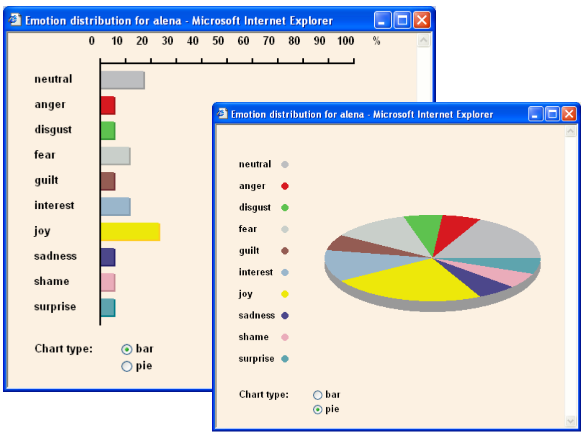



Figure 7.9 Visualization of emotion distribution in two modes

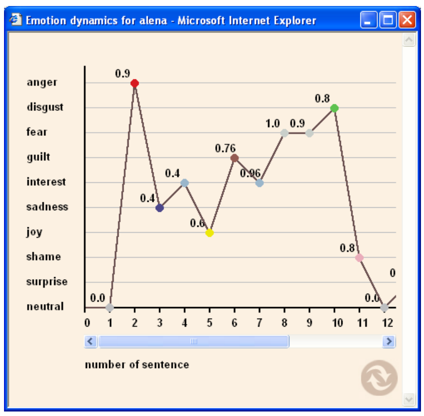



Figure 7.10 Visualization of emotion dynamics

Since the language of online communication is constantly evolving, it is necessary to provide the user of AffectIM with the possibility to add new abbreviations, acronyms, and emoticons to the database. Figure 7.11 shows the windows for adding these symbolic cues to the Affect database.


Figure 7.11 Windows for adding a new emoticon or abbreviation to Affect database

Thus, the implemented AffectIM system provides affect analysis of typed text during online conversations, ensures emotional feedback and complementary visualization of emotion statistics of the conversation flow, and allows users to add new symbolic cue entries to database.

## 7.3 User Study on AffectIM

For the evaluation of the AffectIM system, we conducted a within-subjects experiment (involving comparisons of the same subject under different conditions), in which 20 persons participated in pairs.

### 7.3.1 Experimental Setup

The experiment was designed to compare three AffectIM interfaces using different configuration conditions. For the user study, we prepared three versions of the system:

1. Automatic (A-condition). In this interface, affect sensing from text is performed based on the developed Affect Analysis Model, and corresponding emotional expressions are shown by avatars of communicating persons.
2. Manual (M-condition). During this condition, no automatic emotion recognition from text is performed; users are provided with the possibility to select emotion (and its intensity) to be shown by avatars using "select pop-up menus".
3. Random (R-condition). Instead of showing an arbitrary emotion after each text entry, we decided to introduce some affective intelligence to this interface. The logic behind

random emotion generation algorithm is as follows: first, we process each sentence using Affect Analysis Model, and then we apply two rules: (1) if the output is emotional, we run two functions that randomly select the emotion out of nine available emotions and its intensity, correspondingly; (2) for the case of "neutral" output, we set the function that generates "neutral" emotion with the probability of 60% (during our experiment with Affect Analysis Model we found out that in about 60% of cases of "neutral" outputs our system agreed with at least one human out of three annotators) or "random" emotion with the probability of 40%.

It is also important to note that in each of three interfaces five communicative functions (listed in Section 3.1 and detailed in Section 5.3) are automatically recognized and shown by avatars. In order to keep users' attention on the conversation flow, we intentionally disabled additional functionality of the AffectIM interfaces (such as visualization of emotion distribution and dynamics, display of transcribed text or text annotated by emotions).

Since we had to assign different graphical representations to users, each pair of participants was composed by male and female subjects. Before the experiment, all participants were given instructions (see Appendix C) and their AffectIM IDs and passwords. Each pair of participants was asked to chat online through three interfaces given in random order. Three topics/scenarios (one for each condition) were proposed to subjects:

1. Traveling. "*Please imagine that you and your partner are given 3000 Euros (about 500,000 Yen) in all, and asked to discuss, decide and agree about the country you will visit together. Who knows, …this might be your favorite country, or your partner will convince you of the benefit of choosing his/her country. When you agree on your travel destination, please imagine that you have already reached the destination. Now, you are allowed to do three things together: (1) to talk about, to agree on, and to visit only one place in this country; (2) to select and try only one national dish; (3) to buy only one souvenir in memory of this country.*"
2. Exams. "*We would like you to play a scenario, in which two students, that took the entrance examination to the University last week, just have learned their results and met each other. One of them had passed his/her examination successfully. However, the other student, whose dream was to enter and study in this University, failed his/her test. There are two roles: (1) student who passed the exam; (2) student who failed the exam. Both of them eager to talk and share their feelings about their situation. Please follow the role that experimenter will arbitrary indicate to you, and play this scenario using only your imagination (or real experience) and online communication.*"
3. Food. "*During the life, each person has been trying different kinds of cuisine. Everyone has his/her preferences. Please talk about the dishes, and try to discuss why the ingredients of particular dish harmonize and give savory taste, or, in contrast, mar the taste. What do you prefer: fast-food or home-made food? Maybe, interesting story of your own experience will come from your memory.*"

Each participant was asked to support the conversation flow continuously, and feel free to show emotions in his/her dialog. After each condition, users filled in the corresponding page of the questionnaire and commented on their experience.

### 7.3.2 Evaluation Framework

The main purpose of user study was to evaluate "richness of experience" and "affective intelligence of the system". We hypothesized that user experience and effectiveness of the communication of emotions may benefit from introduction of automatic emotion recognition function and emotionally expressive avatars to IM application.

We compared three AffectIM interfaces along the following dimensions:

1. Interactivity.
2. Involvement (engagement).
3. Sense of copresence (sense of being together with another person in a shared computer-generated environment).
4. Enjoyment.
5. Affective intelligence.
6. Overall satisfaction.

### 7.3.3 Analysis of Results

A total of twenty students and staff from the university (10 males and 10 females) took part in our study. All of them were computer literate, and 19 persons had prior experience with computer based chat or Instant Messaging system. Since IM application is language-based, the main requirement to the participants was to have an appropriate ability to converse in English. The distribution of subjects according to nationality aspect was as follows: 7 subjects from Japan; 3 from Germany; 2 – France; 2 – Iran; 2 – China; 1 – Vietnam; 1 – Malaysia; 1 – Thailand; and 1 subject from Northern Africa.

The average duration of sessions on each interface was 10.1 minutes (minimum 8 and maximum 12.5 minutes), excluding questionnaires.

The questionnaire was divided into four parts, three for each session and one for general questions (for details, see Appendix C). The 11 questions on main criteria were answered based on 7-item agreement Likert scale.

It is worth looking at each measure in detail. Since our study involved each subject being measured under each of three conditions (within-subjects design), we analyzed the data using statistical method ANOVA (an extension of matched pair t-test).

The **interactivity** was measured using statement "*The system was interactive*". The bar graph of means with lines representing standard deviation above and below the mean is shown in Figure 7.12. The results on interactivity in M-condition appear to be a little bit higher than in A-condition, while the minimum level of interactivity was reported in R-condition.

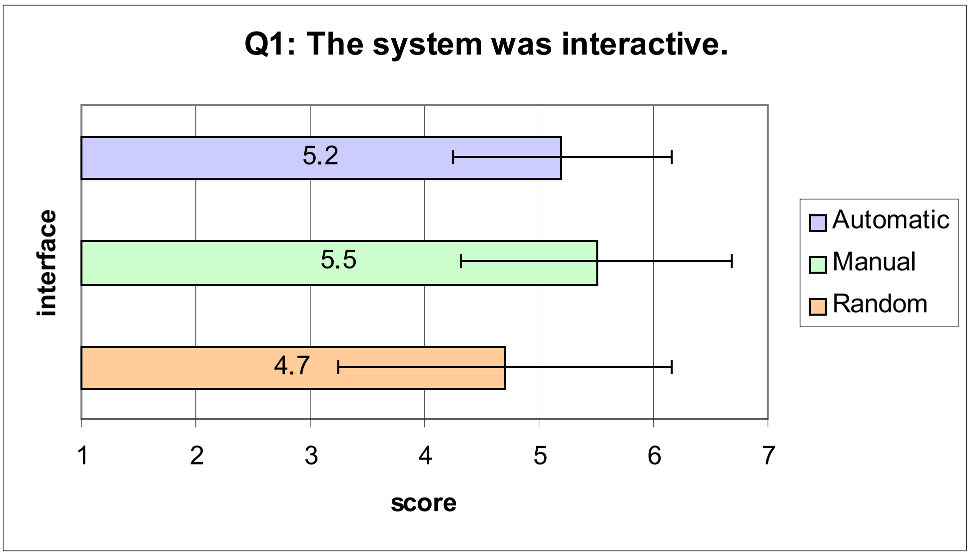



Figure 7.12 Questionnaire results on interactivity (Q1)

Based on the graph alone, we cannot tell whether the interactivity of the interfaces differ significantly. In order to see if the apparent differences between the interfaces are real or due to random chance, we used two-factor ANOVA without replications with chosen significance level $p<0.05$.

The statistic analysis results are shown in Table 7.1, where R, M, and A stand for Random, Manual, and Automatic conditions, respectively; df – degree of freedom (typically, it is one less than the number of sources for comparison); F – F-obtained (measurement of distance between individual distributions); F crit – F-critical value (it is a threshold to which F-obtained is compared); and p – the probability value, which is compared with the significance level (0.05).

Table 7.1 Results of two-factor ANOVA on interactivity (Q1)

| Source | df | F | p | F crit |
|---|---|---|---|---|
| R-M-A | 2 | 2.730 | 0.078 | 3.245 |
| R-M | 1 | 3.730 | 0.068 | 4.381 |
| R-A | 1 | 2.879 | 0.106 | 4.381 |
| M-A | 1 | 0.895 | 0.356 | 4.381 |

Judging from the data, there is no significant difference in interactivity between the three interfaces. However, we can say that M-condition is marginally more interactive than R-condition (p (R-M) = 0.068).

The **involvement (or engagement)** was evaluated using two questionnaire items: “I felt it was important for my conversation partner that I responded after each his/her statement” and “I was awaiting the replies of my conversation partner with true interest”. The mean results of these questionnaire items are shown in Figure 7.13 and Figure 7.14, respectively. The statistic analysis results for involvement are shown in Table 7.2.

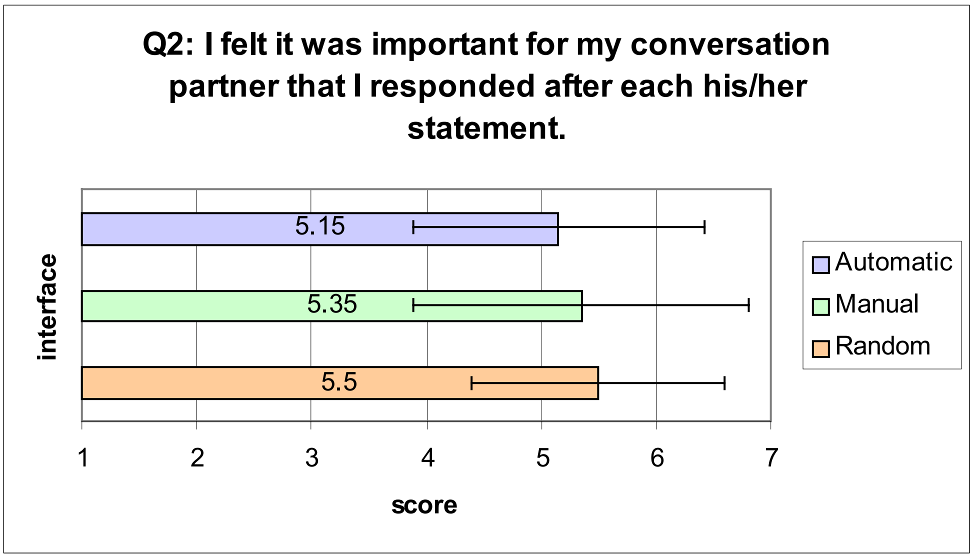



Figure 7.13 Questionnaire results on involvement (Q2)

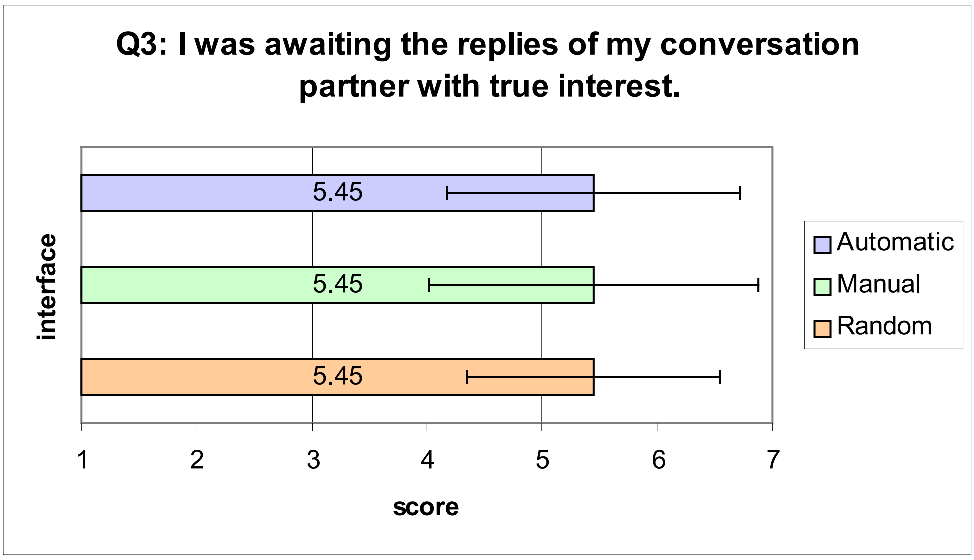



Figure 7.14 Questionnaire results on involvement (Q3)

Table 7.2 Results of two-factor ANOVA on involvement (Q2, Q3)

| Source | df | Q2 | | | Q3 | | |
|---|---|---|---|---|---|---|---|
| | | F | p | F crit | F | p | F crit |
| R-M-A | 2 | 0.468 | 0.630 | 3.245 | 0 | 1 | 3.245 |
| R-M | 1 | 0.163 | 0.691 | 4.381 | 0 | 1 | 4.381 |
| R-A | 1 | 0.823 | 0.376 | 4.381 | 0 | 1 | 4.381 |
| M-A | 1 | 0.369 | 0.551 | 4.381 | 0 | 1 | 4.381 |

It can be seen from statistical analysis that the reported involvement of all three systems does not differ significantly, showing that the level of engagement was almost the same. We can also analyze involvement as an objective measure of automatically recorded information during the sessions. The calculated average of number of characters per minute for dialogs in A-condition was 84, in M-condition – 80, and in R-condition – 74. Since in M-condition participants additionally spent some time for the manual selection of emotion, we can state that objective measure of involvement during A-condition and M-condition was the same, while the average speed of conversations during R-condition was slower.

The following two questionnaire items covering the aspects of space and togetherness are intended for evaluation of **sense of copresence**, or social presence: "*I felt if I were communicating with my conversation partner in the shared virtual space*", "*The system gave me the sense that the physical gap between us was narrowed*". The bar graph represented in Figure 7.15 shows the mean results of first questionnaire item for sense of copresence.

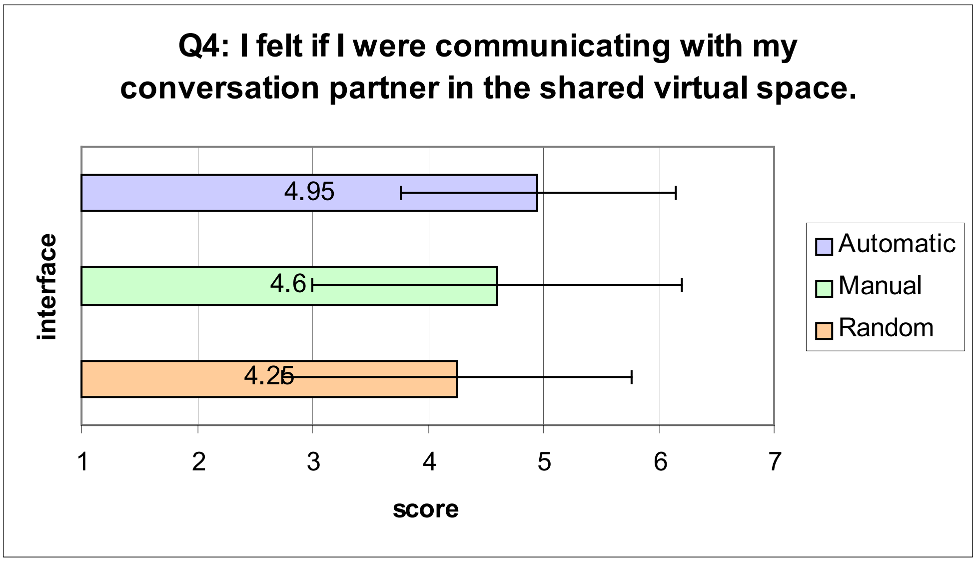



Figure 7.15 Questionnaire results on sense of copresence (Q4)

As seen from the graph, there is evident difference in sense of copresence felt in A-condition and R-condition. The statistic ANOVA results shown in Table 7.3 support the significance of this difference (p (R-A) = 0.023<0.05). We can conclude here that A-condition gave stronger feeling of communication in the shared virtual space than R-condition.

Table 7.3 Results of two-factor ANOVA on sense of copresence (Q4, Q5)

| Source | df | Q4 | | | Q5 | | |
|---|---|---|---|---|---|---|---|
| | | F | p | F crit | F | p | F crit |
| R-M-A | 2 | 2.871 | 0.069 | 3.245 | 1.250 | 0.298 | 3.245 |
| R-M | 1 | 1.274 | 0.273 | 4.381 | 2.209 | 0.154 | 4.381 |
| R-A | 1 | 6.166 | **0.023** | 4.381 | 1.347 | 0.260 | 4.381 |
| M-A | 1 | 1.524 | 0.232 | 4.381 | 0.201 | 0.659 | 4.381 |

The mean results of second questionnaire item for sense of copresence are shown in bar graph represented in Figure 7.16. As seen from the ANOVA results for Q5 (Table 7.3), no significant difference was reported on this statement among three interfaces.

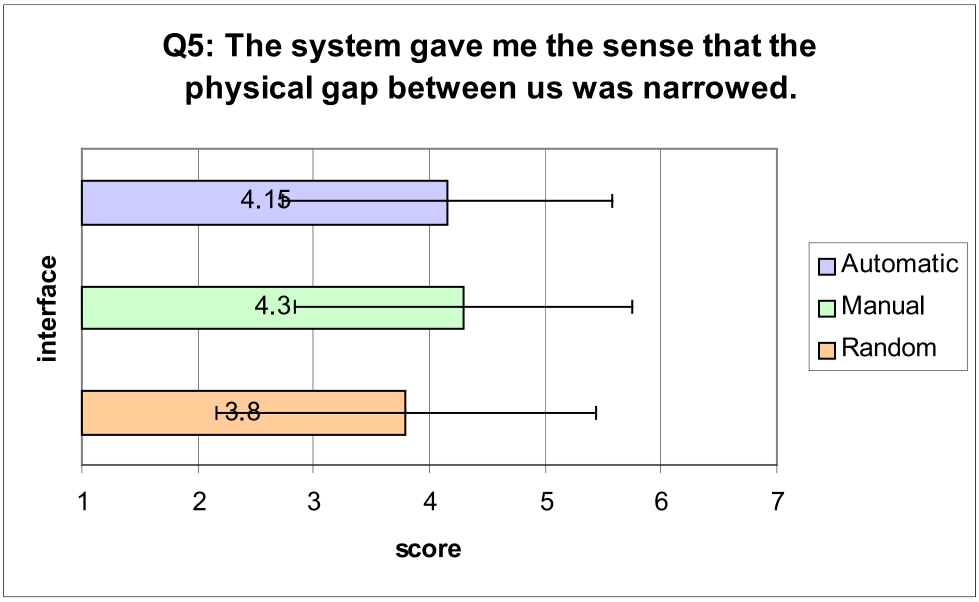



Figure 7.16 Questionnaire results on sense of copresence (Q5)

The level of **enjoyment** was evaluated using the statement "*I enjoyed the communication using this IM system*". The high levels of enjoyment were reported during A-condition and M-condition (Figure 7.17). However, ANOVA resulted in no significant differences among interfaces (see Table 7.4); this indicates that participants almost equally enjoyed using all three IM systems.

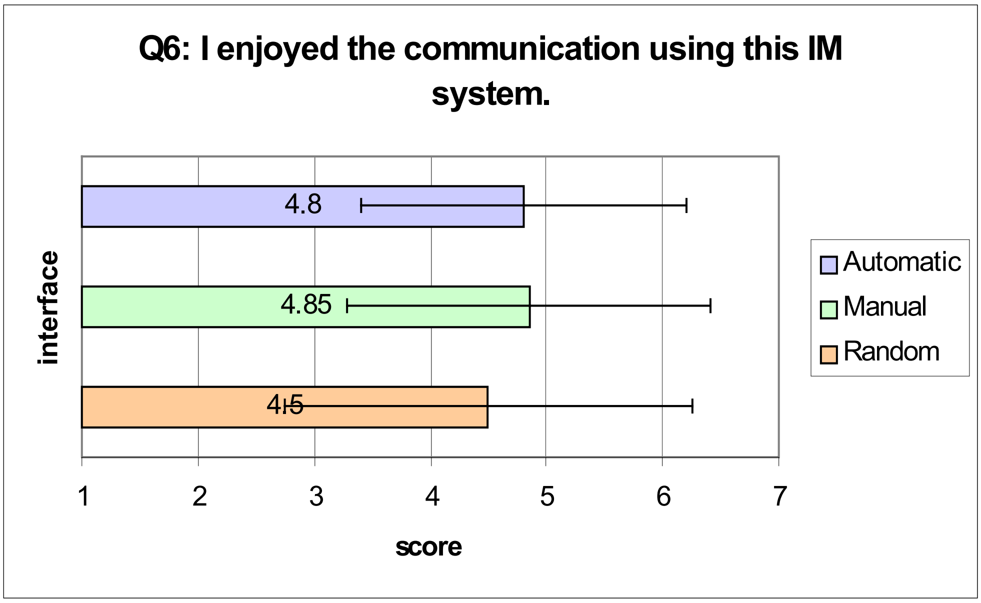



Figure 7.17 Questionnaire results on enjoyment (Q6)

Table 7.4 Results of two-factor ANOVA on enjoyment (Q6)

| Source | df | F | p | F crit |
|---|---|---|---|---|
| R-M-A | 2 | 0.788 | 0.462 | 3.245 |
| R-M | 1 | 1.430 | 0.246 | 4.381 |
| R-A | 1 | 1.132 | 0.301 | 4.381 |
| M-A | 1 | 0.023 | 0.881 | 4.381 |

To evaluate **affective intelligence**, four statements (three – directly related to the system and one – indirectly related) were proposed to subjects in questionnaire: “*The system was successful at conveying my feelings*”, “*The system was successful at conveying my partner’s feelings*”, “*The emotional behavior of the avatars was appropriate*”, and “*I understood the emotions of my communication partner*”. The questionnaire results for these statements are shown in Figure 7.18, Figure 7.19, Figure 7.20, and Figure 7.21, correspondingly.

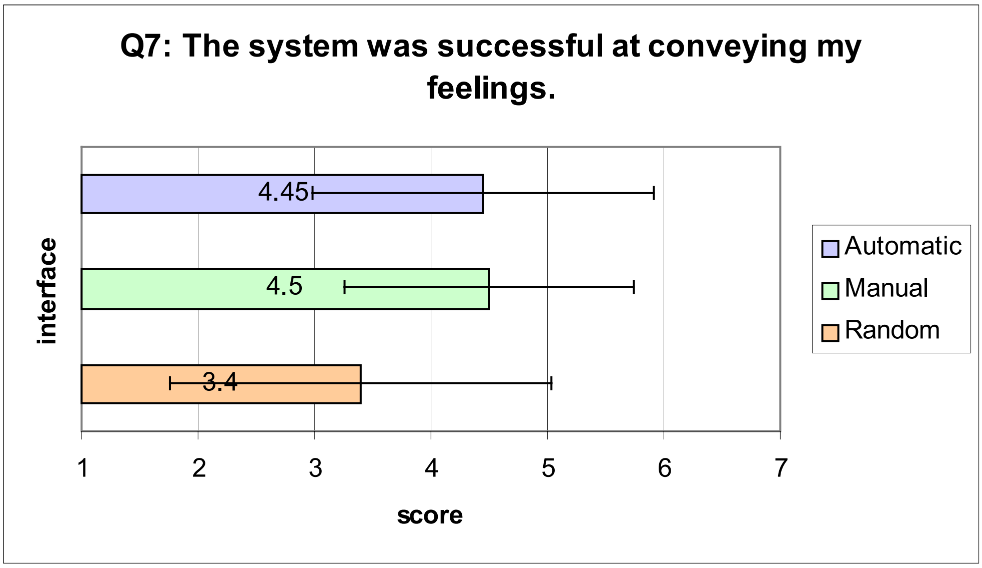



Figure 7.18 Questionnaire results on affective intelligence (Q7)

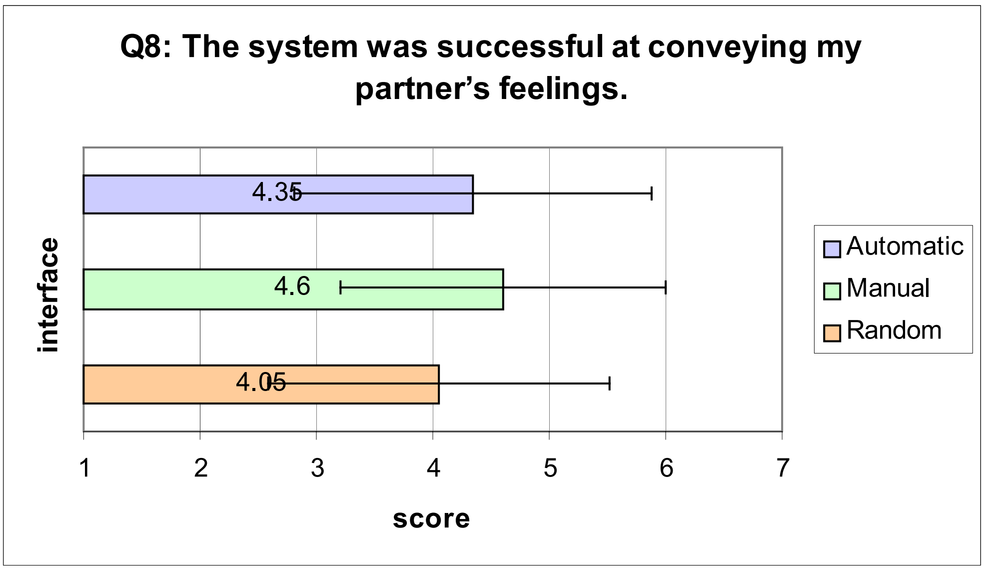



Figure 7.19 Questionnaire results on affective intelligence (Q8)

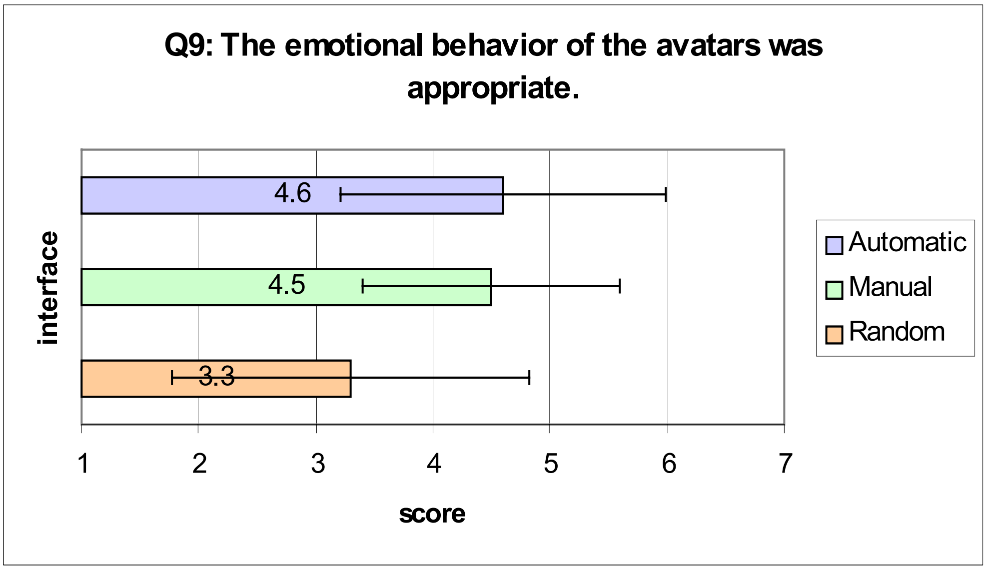



Figure 7.20 Questionnaire results on affective intelligence (Q9)

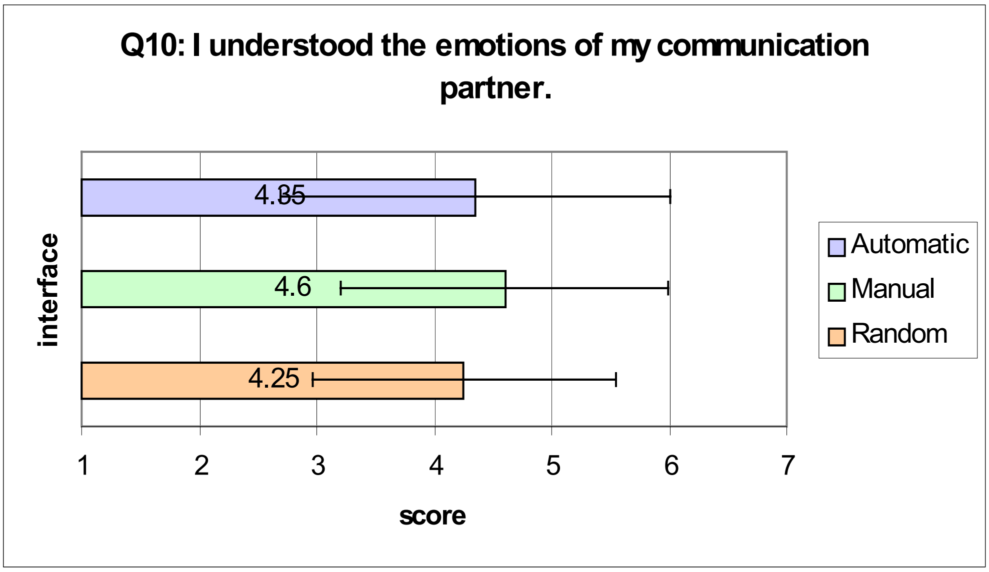



Figure 7.21 Questionnaire results on affective intelligence (Q10)

The ANOVA results for first two statements on affective intelligence are listed in Table 7.5.

Table 7.5 Results of two-factor ANOVA on affective intelligence (Q7, Q8)

| Source | df | Q7 | | | Q8 | | |
|---|---|---|---|---|---|---|---|
| | | F | p | F crit | F | p | F crit |
| R-M-A | 2 | 6.038 | **0.005** | 3.245 | 1.861 | 0.169 | 3.245 |
| R-M | 1 | 8.240 | **0.010** | 4.381 | 3.289 | 0.086 | 4.381 |
| R-A | 1 | 8.923 | **0.008** | 4.381 | 0.851 | 0.368 | 4.381 |
| M-A | 1 | 0.022 | 0.883 | 4.381 | 1.338 | 0.262 | 4.381 |

As seen from Figure 7.18, both systems in A-condition and M-condition (with small prevalence of mean results in M-condition) were more successful at conveying own feelings than system in R-condition. Since M-condition is considered as a "gold standard" in communicating person's emotions, and ANOVA showed no significant difference between M-condition and A-condition (p (M-A) = 0.883>0.05), we might say that automatic emotion recognition system performed well enough to bring high affective intelligence to IM application. As was expected, significant differences were found between R-condition and M-condition (p (R-M) = 0.010<0.05), and between R-condition and A-condition (p (R-A) = 0.008<0.05).

While evaluating successfulness of the interfaces at conveying conversation partner's feelings, the highest rate was given by subjects to M-condition, and the lowest – to R-condition (see Figure 7.19). However, ANOVA for this criterion resulted in no significant difference among all interfaces (p>0.05). One user's comment regarding emotional reactions of partner's avatar was: "I concentrated too much on the reactions of my avatar and not enough on that of my partner. Reading and thinking about the answer took away the concentration on the avatar".

Interesting results were observed for the evaluation of appropriateness of emotional behavior of avatars. As seen from the graph (Figure 7.20) and statistical data of ANOVA (Table 7.6), results for A-condition and M-condition significantly prevailed those for R-condition (p (R-A) = 0.004<0.05; and p (R-M) = 0.004<0.05). Users' comments confirmed that during R-condition subjects sometimes couldn't understand why the avatars did not correspond to their words and reacted in "wrong" ways. Although A-condition was rated a little bit higher than M-condition, no significant difference was detected between these interfaces (p (M-A) = 0.772>0.05).

Table 7.6 Results of two-factor ANOVA on affective intelligence (Q9, Q10)

| Source | df | Q9 | | | Q10 | | |
|---|---|---|---|---|---|---|---|
| | | F | p | F crit | F | p | F crit |
| R-M-A | 2 | 7.789 | **0.001** | 3.245 | 0.627 | 0.539 | 3.245 |
| R-M | 1 | 10.688 | **0.004** | 4.381 | 1.148 | 0.297 | 4.381 |
| R-A | 1 | 11.034 | **0.004** | 4.381 | 0.073 | 0.789 | 4.381 |
| M-A | 1 | 0.087 | 0.772 | 4.381 | 0.922 | 0.349 | 4.381 |

The statement "*I understood the emotions of my communication partner*" measured affective intelligence of the system indirectly, since people used to derive emotional content from text based on semantic information and their empathetic abilities. Emotional expressions of avatars may help to understand the partner's emotion clearer. As was expected, the highest rate was reported in M-condition, and the lowest – in R-condition, where participants might be confused, since sometimes emotions shown by avatar contradict actual emotional content (Figure 7.21). However, no significant difference was found in partner's emotion comprehension among all three interfaces (p>0.05). The possible explanation for such results might be that person typically relies on his/her own affective intelligence rather than on results of artificial affective intelligence. That is why the mean for R-condition appeared relatively high (equals 4.25).

The **overall satisfaction** from using three AffectIM interfaces was evaluated using statement "*I am satisfied with the experience of communicating via this system*". The bar graph of mean results is displayed in Figure 7.22, and ANOVA results are shown in Table 7.7.

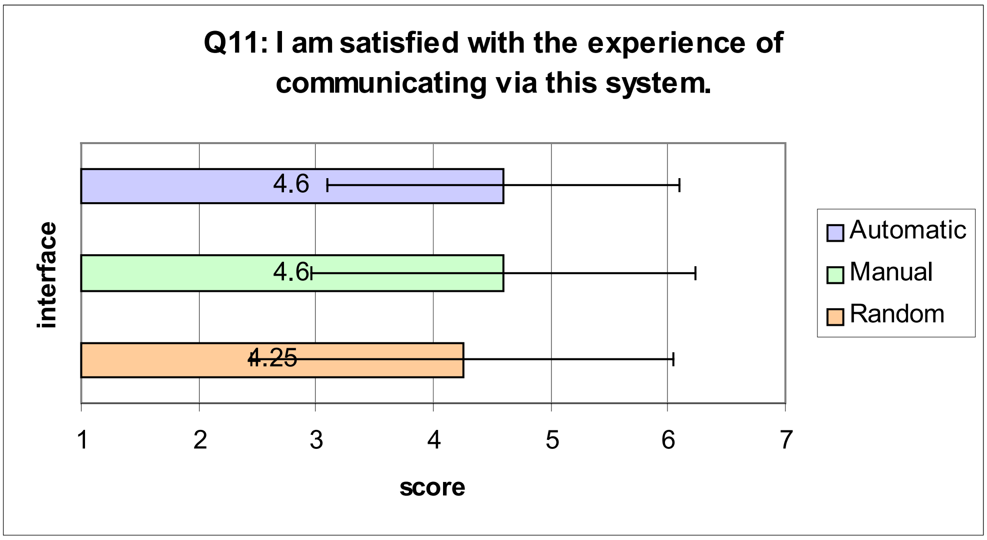



Figure 7.22 Questionnaire results on overall satisfaction (Q11)

As can be seen from the graph, average scores for A-condition and M-condition were equal (4.6), and less satisfaction was reported for R-condition (4.25). The results of ANOVA showed no significant difference ($p>0.05$) in overall satisfaction among interfaces.

Table 7.7 Results of two-factor ANOVA on overall satisfaction (Q11)

| Source | df | F | p | F crit |
|---|---|---|---|---|
| R-M-A | 2 | 0.788 | 0.462 | 3.245 |
| R-M | 1 | 1.430 | 0.246 | 4.381 |
| R-A | 1 | 1.132 | 0.301 | 4.381 |
| M-A | 1 | 0.023 | 0.881 | 4.381 |

In addition to the main questionnaire items, after finishing communications through all three interfaces, participants were given general questions.

Subjects were asked to associate nine emotion states with nine avatar expressions shown on still figures. Female avatar was shown to male subjects, while male avatar was shown to female subjects. The percentages of reported correct associations within males and females are shown in Figure 7.23. As seen from the graph, all 10 female subjects correctly associated 'anger', 'joy', and 'shame' emotions, while all 10 male subjects completely agreed only on 'joy' emotion. 7 females failed to associate 'guilt' emotion, and 9 females failed with 'fear' emotion. For male subjects, the most difficult emotion to associate with avatar expression was 'guilt' (4 males failed). The detected pairs of most often confused emotions are 'fear' – 'surprise' and 'guilt' – 'sadness'; and less often confused emotions are 'guilt' – 'fear' and 'sadness' – 'fear'. Some participants confused emotions in 'interest' – 'joy' and 'surprise' – 'guilt' pairs.

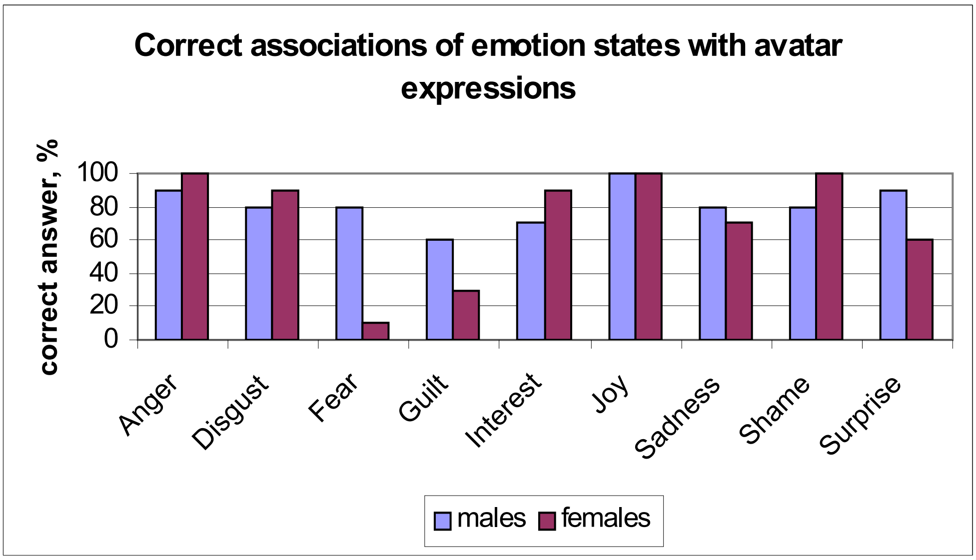



Figure 7.23 Questionnaire results on emotions associated with avatar expressions

These results suggest that during the experiment some participants faced the difficulty with correct interpretations of emotional behavior of avatars.

To the question "*While online, do you use emoticons or abbreviations?*", 19 subjects answered positively. We observed all automatically recorded dialogs, and found out that to some degree the majority of participants used abbreviated language. Regarding emoticons, the total number of such symbolic cues was about 30% higher during A-condition (29 emoticons) than during M-condition and R-condition (19 and 18 emoticons, respectively).

Due to specificity of online communication media, no one can guarantee that users would not make grammatical and syntactical mistakes in text because of fast typing. It is evident that this may worsen the performance of emotion recognition system. In Figure 7.24, the results of answers to the question "*How often do you make spelling mistakes because of fast typing?*" are displayed. As seen from the graph, 70% of female subjects and 60% of male subjects reported high frequency (often or always) of making mistakes. While analyzing the recorded conversations, we detected the following misspelled words that influenced on the result of automatic emotion recognition system and, therefore, on the displayed emotion: "feiled" instead of "failed"; "dispointed" instead of "dissappointed"; "dipressed" instead of "depressed"; "beter" instead of "better", "promissing" instead of "promising", etc.

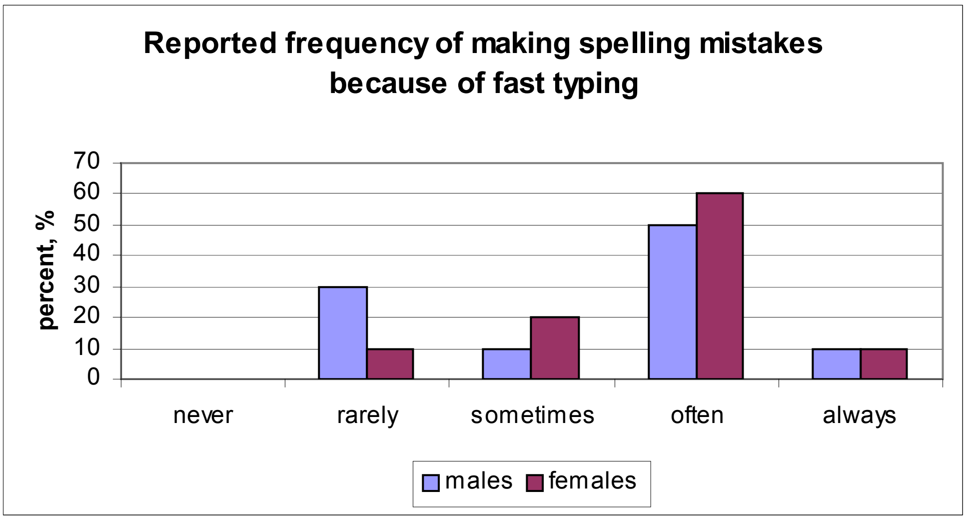



Figure 7.24 Questionnaire results on frequency of making spelling mistakes because of fast typing

The result of answers to the question "*To what degree do you think is necessary to look at a graphical representation of the other communicating person?*" is displayed in Figure 7.25. Below are some explanations of users' points of view:

— "always", because "*it's fun*"; "*to better feel the emotions of the person, also to avoid talking in case it is difficult and send graphical emotions instead of :)*".

— "sometimes", because "*irony is a big problem in written conversation*"; "*graphical representation can help us to understand the partners' emotions between the lines*"; "*as you cannot see your communication partner, an avatar provides at least some sense of physical presence*"; "*if you are unsure how the other person feels, and you want an indication*"; "*text is not enough to express feeling*"; "*I also need to read the text and to think about the next answer*"; "*when I use IM for giving informative matter, I don't need avatar*".

— "rarely", because "*like in Powerpoint, I want to focus on the content, not much on decoration. Most time is spent on interpreting the semantics and the intention/flow of discussion. I tend to extract the information (including emotion) from the text only, with small and quiet intrusions with emoticons. I see the other's avatar as a "third person" indeed...*"; "*the IM I was using so far doesn't provide such feature, so I guess people get used to extract emotions from text*"; "*we usually express our feeling via the messages or emoticons that come with the messages; moreover, when I have a fast conversation, I will focus only on the messages, not the graphical representation*".

These comments suggest that there are two types of IM users: (1) some are open to new features of IM, and find animated graphical representation of a person helpful in understanding the partner's emotions and giving some sense of physical presence; (2) others tend to concentrate their attention on content, and prefer small emotional symbolic cues, like emoticons, to avatar expressions.

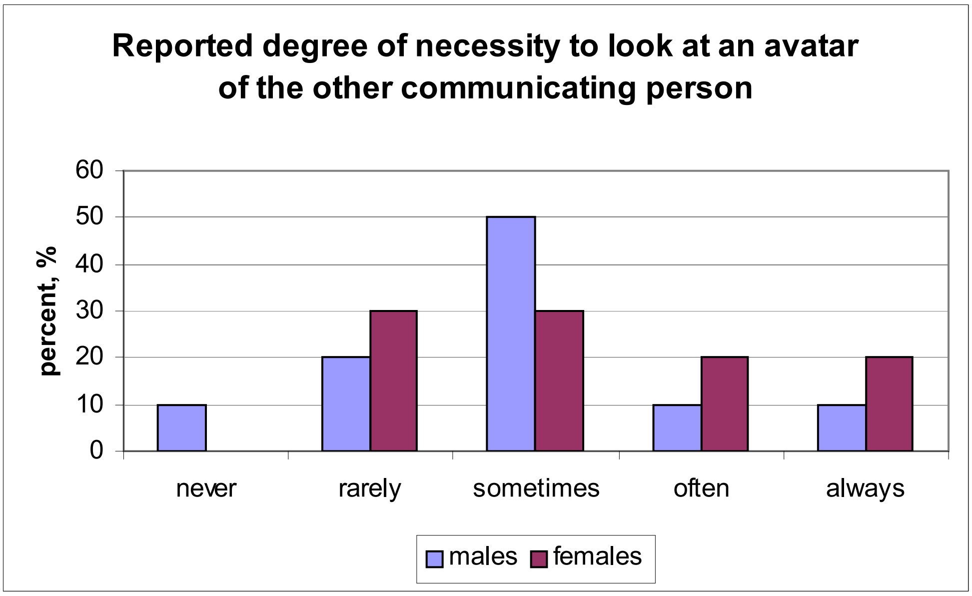



Figure 7.25 Questionnaire results on necessity to look at an avatar of conversation partner

Participants also were asked to indicate either manual selections of emotion state and intensity were helpful or not during M-condition. Only 30% of males and 60% of females answered positively. The result of answers to the question "*How often did you use this function, when you wanted?*" is represented as a bar graph in Figure 7.26. As seen from these data, female subjects used emotion selection function more ardently than male subjects. One female reported "always" use, while two males reported "never" use.

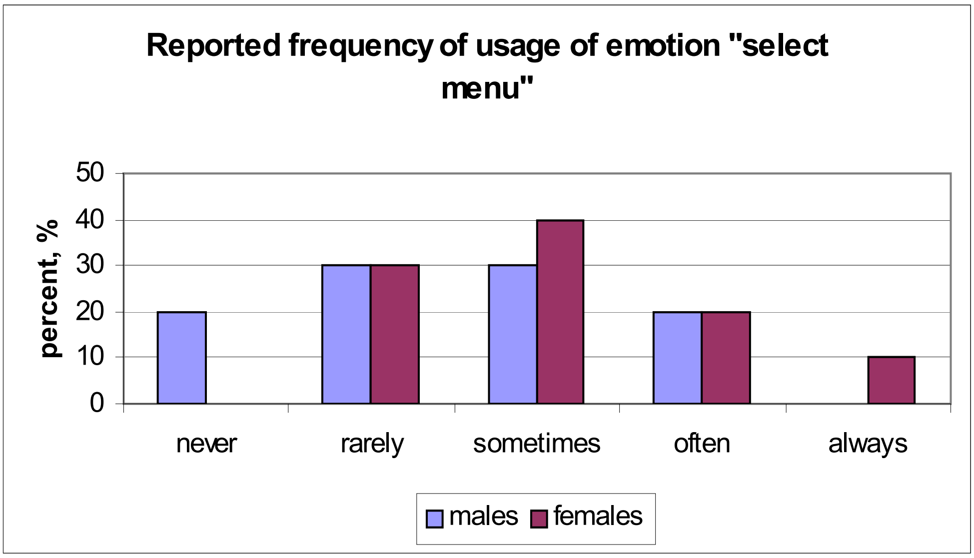



Figure 7.26 Questionnaire results on frequency of usage of emotion "select menu"

The user opinions regarding emotion "select menu" aspect of M-condition were very diverse. Some users criticized the type of pop-up menu, commenting that it was difficult to use, it took long time to select, and choosing emotion intensity on fine-grained scale was overwhelming. For more convenience, they proposed to replace pop-up menus by icons and spread them out to make manual selection function user-friendlier. One of the subjects complained that emotion "select menu" disturbed the flow of the chat. Another reported problem is that since there is no preview of what the emotion expression looks like, it is unclear whether it hits the sentence. Some subjects felt that basic emotions are too general and are not enough to convey emotion in many cases (like, for example, in phrase "hey, just kidding", where users typically use emoticon). Also, they suggested providing the possibility of showing more different or even mixed emotions (somewhat between sadness and joy). However, we think that displaying mixed emotional expressions would add more confusion and misinterpretation to the conversations.

Some subjects underlined positive aspects of manual selection of emotion states. They found this function interesting and helpful, because it offered the possibility to visually express feelings and better understand them, allowed preventing inappropriate emotional reaction of avatar, and guaranteed accuracy of communicated emotion. We can conclude that for the sensitive conversation users would prefer manual control to avoid system mistakes that could sometimes harm the conversation.

Regarding the users' general impressions from using AffectIM system, they found automatic recognition and visual representation of emotions to be a good, promising idea and funny to watch. The representation of emotions through the avatars was interesting, pretty clear and easy to understand, however, some participants reported the difficulty of distinguishing the displayed emotions and stated that system would benefit from better customizable avatars or even abstract avatars like smileys. Several users commented that they would also like to express wider range of emotions.

During our experiment with the AffectIM system we got many valuable results and feedbacks, and investigated new ways of improvements. The data obtained shows that the developed emotion recognition engine worked with good level of reliability, so that there was no significant difference between system providing automatic emotion sensing from text and system with manual control of emotional behavior of avatars (so called "gold standard"). It is evident that AffectIM will benefit from integration of both these functions in one interface, where they can complement each other and provide user with the ability to select between two modes (automatic or manual control of emotion expressions) depending on type and sensitivity of conversation.

# Chapter 8

# Discussion and Conclusions

The purpose of presented work is to improve expressiveness and interactivity of computer-mediated communication. This thesis introduces a new rule-based syntactical approach to affect recognition from text messaging. Typically, researchers in this field deal with grammatically and syntactically correct textual input. By contrast, our analysis of affect expressed through written language is inspired by the evolving language, style and specifics of IM conversations. For textual input processing, the developed Affect Analysis Model handles not only correctly written text, but also informal messages written in abbreviated or expressive manner.

In order to support the handling of abbreviated language and the interpretation of affective features of emoticons, abbreviations, and words, a special Affect database was created.

The proposed rule-based algorithm for affect sensing from text processes each sentence in sequential stages, including symbolic cue processing, detection and transformation of abbreviations and acronyms, sentence parsing, and word/phrase/sentence-level analyses. Our method is able to process different types of sentences, including simple, compound, complex (with complement and relative clauses), and complex-compound sentences. Affect in text is classified into nine emotion categories (or neutral), and information that can be displayed by avatar gestures as social communicative behaviour is identified. The strength of the resulting emotional state depends on emotional vectors of words, relations among them, tense of analysed sentence and availability of first person pronouns.

The salient features of the proposed algorithm are:

1. analysis of nine emotions on the level of individual sentences;
2. the ability to handle the evolving language of online communications;
3. basis on database of affective words, interjections, emoticons, abbreviations and acronyms, modifiers;
4. vector representation of affective features of words, phrases, clauses and sentences;

5. consideration of syntactic relations and dependences between words in a sentence;
6. analysis of negation, modality, and conditionality;
7. consideration of relations between clauses in compound, complex, or complex-compound sentences;
8. emotion intensity estimation.

The developed system showed promising results on affect recognition in real examples of online conversation. In a study based on 160 sentences, the system result agreed with at least two out of three human annotators in 70% of the cases.

In order to enrich the user's experience in online communication, make it enjoyable, exciting and fun, we realized a web-based IM application, AffectIM, and endowed it with the emotional intelligence by integrating with the Affect Analysis Model. Researchers argue that there is a positive relationship between the amount of IM use and verbal, affective, and social intimacy [29]. Marcel [47] characterized the intimacy in the following words: "Even if I cannot see you, if I cannot touch you, I feel that you are with me". In our work, we strive to provide vivid and expressive visual signals to enhance socially oriented online communication media. To realize visual reflection of textual affective information, we have designed two animated avatars (graphical representations of a user) performing various expressive patterns (emotions, social behavior, and natural idle movements), contributing thus to greater interactivity. The developed AffectIM supports online communication, allows users to see the conversation flow in three modes (plain text, transcribed text, or text annotated with emotion), and visualizes the communicated emotions, emotion distribution and emotion dynamics.

The 20-person user study conducted on AffectIM showed that the IM system with automatic emotion recognition function performed well enough to bring high affective intelligence to IM application. Part of the participants considered animated graphical representation of a person helpful in understanding the partner's emotions and giving some sense of physical presence. Users reported that their experience with AffectIM was fun and interesting. From this experiment we found out that IM application might benefit from integration of automatic emotion sensing engine with manual control of emotional behavior of avatars in one interface, which will allow users to select between two modes depending on type and sensitivity of conversation.

The main limitations of the developed affect recognition module are: strong dependency on the created source of lexicon, Affect database; no disambiguation of word meanings; disregard of contextual information; and inability to recognize and process misspelled words in a sentence. In our future study we will investigate those issues and explore the possibilities to overcome current limitations of the system.

To improve the developed system, we are planning to extend Affect database by indirectly emotion-related words, to realize smoothening functions for the evaluation and visualization of emotion dynamics, to study cultural differences in perceiving and expressing emotions, and to integrate text-to-speech engine with emotional intonations into developed IM application.

Since the study described in this dissertation was concentrated on the tasks of recognition and interpretation of affect communicated through text, and developed emotion identification methodology can provide quantitative, empirical grounding for emotional text generation, the future research might be focusing on how emotion is generated and expressed through text. The main idea is devoted to the research on Emotional Natural Language Generation, and particularly, on affect text generation for empathetic advisory dialogue.

The following stages of future research are planned to realize:

1. Investigation of the background of the affect text generation for advisory dialogue; and survey of the related works in the field of Emotional Natural Language Generation.
2. Analysis of psychologically inspired emotional models; definition and employment of the appropriate one.
3. Investigation of lexical, syntactic and semantic properties that are correlated with specific emotions. Here, some aspects of the developed Affect Analysis Model might be taken into consideration.
4. Development of a method of varying language depending on emotions.
5. Study and proposal of new techniques of the content determination, discourse planning, sentence aggregation, lexicalization, referring expression generation, and linguistic realization.
6. Suggestion of techniques based on corpus analysis that can be used to acquire the various kinds of knowledge needed in order to build Emotional Natural Language Generation system.
7. Development of the affective advisory dialogue system that is capable of generating the affective text through employment of rule-based heuristics that define when and how empathy elements have to be introduces in the text. As possible applications, we consider the followings: legal adviser system (ensuring not only special consultations, but also empathetic impact inspiring humans), game-like system enabling child to cognize the emotion-colored world, virtual agency as space to communicate with variety of affective agents.

The secondary topic of my future research is to create and employ animated life-like character capable of giving not only verbal, but also visual feedback to a user. The following requirements impose a number of conversational capabilities on any spoken dialogue interface with a believable life-like character: (1) to have a personality; (2) to be capable of showing emotion; (3) to exhibit social intelligence; (4) to have some self-motivation; (5) to have memory; (6) to be able to adapt to new situations; (7) to have some consistency of expression; (8) to provide a sense of friendliness, etc. In the future study, I will follow these requirements in order to support emotion, social behavior, memory, and other functions of the agent, and to create an effective visual display to a user.

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# Appendix A: Emotional State Gradation within Intensity Levels

**ANGER**

**0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0**

**neutral annoyed irritated indignant angry enraged**

**DISGUST**

**0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0**

**neutral dislike disgust hate**

**FEAR**

**0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0**

**neutral apprehensive afraid terrified**

**GUILT**

**0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0**

**neutral regret fault guilt compunction self-reproach**

**INTEREST**

**0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0**

**neutral interesting attractive involving desirous**

**JOY**

**0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0**

**neutral cheerful glad happy joyful elated**

**SADNESS**

**0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0**

**neutral wistful doleful unhappy sad depressed**

**SHAME**

**0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0**

**neutral confusion embarrassment shame disgrace dishonour**

**SURPRISE**

**0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0**

**neutral unexpectedness wonder astonishment surprise amazement**

# Appendix B: The Sentences Annotated by Human Raters and Analyzed by Affect Analysis Model

| | Sentence | Dominant emotion and corresponding intensity / Communicative function | | | |
|---|---|---|---|---|---|
| | | Rater 1 | Rater 2 | Rater 3 | AAM* |
| 1 | And you need alternative views to form a fair opinion :-p | Joy:0.3 | Joy:0.2 | Joy:0.3 | Joy:0.2 |
| 2 | I dreamed I was running around being chased by a giant bee sting. | Surprise:0.8 | Neutral:0.0 | Surprise:1.0 | Fear:0.4 |
| 3 | It's funny how when your neighbor from senegal sings to herself in the shower in french, it makes your life a lot better. | Joy:1.0 | Joy:0.2 | Surprise:0.5 | Joy:0.64 |
| 4 | so i am a pretty tired kid today. | Sadness:0.6 | Sadness:0.3 | Sadness:0.2 | Sadness:0.38 |
| 5 | i am ready for my art history final, but i am afraid of the other ones. | Fear:0.7 | Fear:0.7 | Fear:0.6 | Fear:0.8 |
| 6 | I also got her 4 pairs of socks cuz [cause] hers all have holes, and that annoys me to no end for some reason lol [laughing out loud]. | Joy:1.0 | Joy:0.6 | Joy:0.6 | Joy:1.0 |
| 7 | AND I M [am] NOT SINGING HAPPILY TODAY | Sadness:0.5 | Sadness:0.3 | Sadness:0.7 | Neutral:0.0 |
| 8 | We need choices in life. | Neutral:0.0 | Neutral:0.0 | Neutral:0.0 | Neutral:0.0 |
| 9 | It's fun to shop, especially when you know you won't pay for it. | Joy:0.7 | Joy:0.2 | Joy:0.9 | Joy:0.64 |
| 10 | Sis [sister] had booked her chalet for her birthday. | Neutral:0.0 | Neutral:0.0 | Neutral:0.0 | Joy:0.04 |
| 11 | They've got an amazing spread of all-time local favourites. | Surprise:1.0 | Surprise:0.8 | Surprise:0.9 | Surprise:0.8 |
| 12 | oh yes, not forgetting, they had a mini chocolate fountain! | Surprise:0.5 | Surprise:0.3 | Joy:1.0 | Neutral:0.0 |
| 13 | i was so delighted to see it. | Joy:0.9 | Joy:0.8 | Joy:1.0 | Joy:1.0 |
| 14 | it made me pretty sad, but it was a really good movie. | Joy:0.4 | Joy:0.2 | Sadness:0.4 | Joy:0.19 |
| 15 | Where did we go wrong? | Sadness:0.3 / PAQ** | Neutral:0.0 / PAQ** | Surprise:0.4 / PAQ** | Neutral:0.0 / PAQ** |
| 16 | I'm excited to hear of news from many travelers, despite my jealousy. | Interest:0.7 | Joy:0.5 | Joy:0.7 | Interest:0.9 |
| 17 | to talk more about money, my credit card info got stolen online. | Sadness:0.6 | Sadness:0.6 | Anger:0.9 | Sadness:0.4 |
| 18 | i feel violated, and more poor. | Sadness:0.9 | Sadness:0.5 | Sadness:1.0 | Sadness:0.4 |
| 19 | this morning i went up on the roof to get some sun on my pasty white legs, and i burned them. | Sadness:0.6 | Sadness:0.4 | Surprise:0.3 | Sadness:0.32 |
| 20 | I'm still concluding that it was all false advertising from the beginning, how deceiving. | Sadness:0.3 | Sadness:0.4 | Anger:1.0 | Sadness:0.4 |
| 21 | Then later that night my jaw started hurting really bad. | Sadness:1.0 | Sadness:0.6 | Sadness:0.8 | Sadness:0.72 |
| 22 | collage is ruining my life a little. | Sadness:0.3 | Sadness:0.3 | Sadness:0.5 | Sadness:0.18 |
| 23 | The melody is very gentle and hearty, it gives you the shiver. | Joy:0.4 | Joy:0.6 | Surprise:0.8 | Joy:0.22 |
| 24 | My friends are definitely the most important things to me. | Interest:0.5 | Interest:0.7 | Interest:0.9 | Interest:0.5 |
| 25 | Although I've only mentioned eight friends, I have many more that I cherish. | Joy:0.4 | Joy:0.1 | Interest:0.4 | Interest:0.4 |
| 26 | I GET MY LICENSE TODAY!!!!! | Joy:1.0 | Joy:0.7 | Joy:1.0 | Surprise:0.72 |
| 27 | Something seems very wrong with my body. | Fear:0.5 | Fear:0.2 | Disgust:0.9 | Sadness:0.45 |
| 28 | why does this have to be so hard?! | Sadness:1.0 | Sadness:0.5 / PAQ** | Disgust:0.6 | Sadness:1.0 / PAQ** |
| 29 | i have my math exam tomorrow, and I m [am] terrified. | Fear:1.0 | Fear:1.0 | Fear:1.0 | Fear:1.0 |

| | | | | | |
|---|---|---|---|---|---|
| 30 | Well, I've completely destroyed the idea of eating lightly. | Sadness:0.8 | Sadness:0.2 | Guilt:0.6 | Sadness:1.0 |
| 31 | I shall pick Joci up and amuse her, then fall asleep. | Interest:0.2 | Interest:0.5 | Interest:0.6 | Interest:0.64 |
| 32 | I can't bring myself to really care that I probably failed my biology test. | Neutral:0.0 | Neutral:0.0 | Sadness:0.7 | Neutral:0.0 |
| 33 | My brother broke my toe or some other random foot bone. | Anger:0.5 | Sadness:0.4 | Anger:0.4 | Sadness:0.56 |
| 34 | Yes, this is interesting, I m [am] once again in the position to choose from a lot of girls to be with. | Interest:0.4 | Interest:0.3 | Interest:1.0 | Interest:0.32 |
| 35 | I eat when I'm angry, sad, bored… | Neutral:0.0 | Neutral:0.0 | Neutral:0.0 | Neutral:0.0 |
| 36 | Still thinking of that beauteous breakfast we had this morning and the jasmines on the way home. | joy:0.6 | Joy:0.2 | Joy:0.8 | Neutral:0.0 |
| 37 | I always seem to miss her, no matter how often I see her, which makes her decision to go to Northeastern all the more depressing. | Sadness:1.0 | Sadness:0.9 | Sadness:0.9 | Sadness:0.7 |
| 38 | I went to party today, but nothing exciting happened there. | Neutral:0.0 | Neutral:0.0 | Surprise:0.3 | Neutral:0.0 |
| 39 | I think my friends have made me a good person, even if I am a lame one, and I am thankful for them. | Neutra:0.0 / thanks | Joy:0.2 | Joy:0.6 | Joy:0.6 |
| 40 | They almost did an attack, but we luckily got away! | Joy:0.8 | Joy:0.5 | Joy:0.5 | Joy:0.77 |
| 41 | Yeah, I don't want to go to school… | Sadness:0.2 | Disgust:0.3 | Disgust:0.8 | Neutral:0.0 |
| 42 | Why must life be so full of pain? | Sadness:1.0 | Sadness:0.6 / PAQ** | Sadness:1.0 | Neutral:0.0 / PAQ** |
| 43 | I love you and i couldn't live without you, but i can't stand your bullshit right now | Disgust:0.7 | Disgust:0.6 | Disgust:1.0 | Neutral:0.0 |
| 44 | I just met you, and you r [are] so cool. | Interest:0.8 | Interest:1.0 | Interest:1.0 | Interest:0.61 |
| 45 | I will never forgive you, and you will always be left in my memory as a sad pathetic man. | Disgust:1.0 | Disgust:1.0 | Disgust:1.0 | Sadness:0.72 |
| 46 | Even though the house was a mess, I was just so happy. | Joy:1.0 | Joy:0.6 | Joy:1.0 | Joy:0.48 |
| 47 | I'm just hoping she's cute, cause all the Shitzuh's I've seen so far were butt ugly. | Interest:0.5 | Interest:0.3 | Disgust:0.4 | Disgust:0.4 Interest:0.4 |
| 48 | I have feelings of regret for leaving it all behind in the dust. | Guilt:0.7 | Guilt:0.2 | Guilt:0.7 | Guilt:0.2 |
| 49 | But he is the one that is lying. | Anger:0.7 | Disgust:0.4 | Anger:0.8 | Sadness:0.16 |
| 50 | All I can do is sit and pretend. | Neutral:0.0 | Neutral:0.0 | Shame:0.2 | Shame:0.08 |
| 51 | I never loved nobody fully. | Neutral:0.0 | Neutral:0.0 | Sadness:1.0 | Neutral:0.0 |
| 52 | On Friday, Dennis and his friends smashed his first guitar because apparently it never worked or something so. | Sadness:0.4 | Neutral:0.0 | Surprise:0.6 | Sadness:0.22 |
| 53 | I offered to pay for her movie ticket as an early birthday present because it's her birthday the next day, and she readily agreed. | Joy:0.3 | Joy:0.2 | Interest:0.7 | Joy:0.08 |
| 54 | It's really heartening to know that there are people who are genuine and who care in class through the little things we do. | Joy:0.3 | Neutral:0.0 | Joy:0.6 | Joy:0.38 |
| 55 | Sometimes I just think about how different the people in class are, yet I enjoy the company of these people because of their differences. | Joy:0.5 | Joy:0.2 | Joy:0.7 | Joy:0.6 |
| 56 | Every one of us has the potential to touch hearts. | Interest:0.2 | Neutral:0.0 | Joy:0.6 | Interest:0.5 |
| 57 | Anyway, they didn't wake up, which is surprising because Brak screams like a girl when he's just had freezing cold water chucked on him. | Surprise:0.8 | Surprise:0.7 | Surprise:0.7 | Surprise:0.72 |
| 58 | i think somewhere along the way in the 15 yrs [years] of marriage he forgot about me... | Sadness:0.2 | Sadness:0.4 | Sadness:1.0 | Neutral:0.0 |
| 59 | At first she seemed fine, but when she tried to move she complained about her arm killing her. | Sadness:0.5 | Sadness:0.4 | Sadness:0.6 | Fear:0.4 |
| 60 | I stepped aside and cried a little, so that she wouldn't see me | Sadness:0.6 | Sadness:0.6 | Shame:0.8 | Sadness:0.28 |
| 61 | Jacquin said to me that it was funny how Rauncie's | Joy:0.8 | Joy:0.1 | Surprise:0.7 | Joy:0.32 |

| | | | | | |
|---|---|---|---|---|---|
| | name sounds like raunchy. | | | | |
| 62 | It hurts to live out a mistake that you are constantly reminded of. | Sadness:1.0 | Sadness:0.6 | Shame:1.0 | Sadness:0.72 |
| 63 | There are no other terms that could really put me in a better position. | Sadness:0.3 | Sadness:0.2 | Joy:0.9 | Neutral:0.0 |
| 64 | Why is every path at every point of my life the hard one? | Sadness:1.0 / PAQ** | Sadness:0.6 / PAQ** | Sadness:1.0 | Sadness:0.6 / PAQ** |
| 65 | I'd like to go home to visit my friends and family, but can't justify the ticket purchase | Sadness:0.1 | Sadness:0.1 | Sadness:1.0 | Neutral:0.0 |
| 66 | Keep your head up, Kyle, it will get better. | Joy:0.3 | Joy:0.1 | Joy:0.4 | Neutral:0.0 |
| 67 | Like most guys, I love fast cars even though I don't drive one. | Joy:0.8 | Joy:0.4 | Interest:0.7 | Joy:0.9 |
| 68 | I am afraid to go out at night, no matter how big a group I am with. | Fear:0.7 | Fear:0.7 | Fear:1.0 | Fear:0.8 |
| 69 | I am ashamed that this is what my country has become. | Shame:0.6 | Shame:0.6 | Shame:1.0 | Shame:0.5 |
| 70 | i am stressed becuz [because] i have frequent headaches | Sadness:1.0 | Sadness:0.6 | Sadness:0.8 | Sadness:0.6 |
| 71 | we were sharing a laugh with a stranger | Joy:0.8 | Joy:0.6 | Joy:1.0 | Joy:0.8 |
| 72 | And I thought of dad, and my heart broke within me. | Sadness:0.7 | Sadness:0.8 | Sadness:1.0 | Sadness:0.56 |
| 73 | My speech was at the last part of the lesson, so i was worrying and worrying | Fear:0.4 | Fear:0.2 | Fear:1.0 | Fear:0.16 |
| 74 | I m [am] so in love with the mussels with garlic and lemon butter! | Joy:0.7 | Joy:0.6 | Interest:0.8 | Joy:1.0 |
| 75 | if only my brain was like a thumbdrive, how splendid it would be. | Neutral:0.0 | Neutral:0.0 | Sadness:0.1 | Neutral:0.0 |
| 76 | I have to look over my astronomy notes for about 10 minutes, but this thing from Colleen totally distracted me. | Sadness:0.6 | Sadness:0.4 | Disgust:0.1 | Sadness:0.32 |
| 77 | there was a little emotional disaster between myself and my new bf [boyfriend] | Sadness:0.4 | Sadness:0.1 | Sadness:0.4 | Sadness:0.14 |
| 78 | The salesperson was really friendly and helpful | Joy:0.5 | Joy:0.1 | Joy:1.0 | Joy:0.13 |
| 79 | When you are in love, the mind and heart never shut down. | Neutral:0.0 | Neutral:0.0 | Joy:1.0 | Neutral:0.0 |
| 80 | this summer will be very interesting indeed..... | Interest:0.7 | Interest:0.2 | Interest:1.0 | Neutral:0.0 |
| 81 | the rest of my life is in shambles, but it's all my own fault. | Guilt:0.5 | Sadness:0.6 | Guilt:1.0 | Guilt:0.6 |
| 82 | someone suggested that it is inappropriate for me to participate in this discussion | Sadness:0.1 | Neutral:0.0 | Surprise:0.5 | Sadness:0.1 |
| 83 | I apologized to him. | Guilt:0.4 | Guilt:0.2 | Guilt:1.0 | Guilt:0.4 |
| 84 | He's probably going to fail me or give me a bad grade. | Sadness:0.4 | Fear:0.3 | Fear:0.8 | Sadness:0.9 |
| 85 | I am the luckiest man alive. | Joy:1.0 | Joy:0.6 | Joy:1.0 | Joy:1.0 |
| 86 | last sunday was the graduation ceremonies, and i was ecstatic about it... | Joy:0.7 | Joy:0.8 | Joy:1.0 | Joy:0.8 |
| 87 | i wasn't satisfied by the pictures my sister took during my graduation | Neutral:0.0 | Anger:0.3 | Anger:0.7 | Neutral:0.0 |
| 88 | i seriously do not understand how ppl [people] can be around negative ppl. | Neutral:0.0 | Neutral:0.0 | Disgust:1.0 | Neutral:0.0 |
| 89 | I love my ipod to death. | Joy:1.0 | Joy:0.7 | Interest:1.0 | Joy:0.9 |
| 90 | Consecutive holidays of the beginning of May might be the enjoyments for a general person. | Neutral:0.0 | Neutral:0.0 | Neutral:0.0 | Neutral:0.0 |
| 91 | I hate worms. | Disgust:1.0 | Disgust:1.0 | Disgust:1.0 | Disgust:0.9 |
| 92 | This journey seems to be bothering her | Neutral:0.0 | Neutral:0.0 | Disgust:0.6 | Anger:0.4 |
| 93 | I am helpless in this situation and do not know what to do. | Fear:0.4 | Neutral:0.0 | Fear:1.0 | Sadness:0.3 |
| 94 | there are many obstacles to overcome | Sadness:0.3 | Sadness:0.2 | Fear:0.5 | Sadness:0.24 |
| 95 | she is now with no troubles, they are all left behind. | Neutral:0.0 | Neutral:0.0 | Joy:0.7 | Neutral:0.0 |
| 96 | I'm super scared by wisdom tooth extraction. | Fear:1.0 | Fear:1.0 | Fear:1.0 | Fear:0.9 |
| 97 | I wanna let you know how much I feel your pain. | Sadness:1.0 | Sadness:0.2 | Sadness:0.9 | Neutral:0.0 |

| | | | | | |
|---|---|---|---|---|---|
| 98 | For a long time, I thought my own mother was perhaps the saddest creature I had ever encountered. | Neutral:0.0 | Neutral:0.0 | Sadness:1.0 | Neutral:0.0 |
| 99 | He was acting without remorse | Neutral:0.0 | Neutral:0.0 | Neutral:0.0 | Neutral:0.0 |
| 100 | me and Brandon just broke up. | Sadness:0.7 | Sadness:0.3 | Sadness:0.5 | Sadness:0.56 |
| 101 | he is like WOW. | Surprise:1.0 | Surprise:0.9 | Interest:1.0 | Surprise:0.96 |
| 102 | I was totally miserable last summer | Sadness:0.9 | Sadness:0.5 | Sadness:1.0 | Sadness:0.86 |
| 103 | slicing all those strawberry cakes is annoying, especially when there is always orders coming in | Anger:0.3 | Anger:0.2 | Disgust:0.4 | Anger:0.24 |
| 104 | the boss is always bitching about how we use too much pepper, too much cheese, paper towels, etc... | Anger:0.7 | Disgust:0.3 | Disgust:1.0 | Sadness:0.4 |
| 105 | An unrelated act of terror results in perhaps an unpreventable, albeit unjust, war. | Fear:1.0 | Fear:0.8 | Sadness:0.8 | Neutral:0.0 |
| 106 | The music was great, and i could feel myself gasping for air on the dance floor | Joy:0.7 | Joy:0.3 | Joy:1.0 | Surprise:0.36 |
| 107 | Forgive my soul for being weak. | Guilt:0.9 | Guilt:0.6 | Sadness:0.9 | Joy:0.2 |
| 108 | Kate was the worst mistake of my life. | Sadness:0.6 | Sadness:0.5 | Shame:1.0 | Sadness:0.45 |
| 109 | today was Richie’s birthday and I said Happy Birthday every time I saw him, but it annoyed him. | Sadness:0.2 | Sadness:0.3 | Surprise:0.5 | Anger:0.08 |
| 110 | I feared any product with the word “cream” in it. | Fear:0.6 | Fear:0.6 | Fear:0.6 | Fear:0.64 |
| 111 | Actually, I do feel a lot healthier on this diet. | Joy:0.7 | Joy:0.3 | Joy:1.0 | Joy:0.48 |
| 112 | I envy those who have a real marriage, but I’m also happy for them. | Joy:0.6 | Joy:0.4 | Shame:0.5 | Joy:0.6 |
| 113 | She’s getting prettier every minute | Interest:0.8 | Joy:0.3 | Joy:1.0 | Joy:0.48 |
| 114 | Despite his endless demonstrations of rude power, brotherly love always prevails. | Joy:0.6 | Joy:0.1 | Joy:0.1 | Joy:0.8 |
| 115 | my Dad is going to come home and start yelling at anyone. | Fear:0.5 | Fear:0.2 | Shame:0.6 | Fear:0.2 |
| 116 | Oh no, this is getting stressful around here. | Sadness:0.8 | Sadness:0.3 | Disgust:0.4 | Sadness:0.64 |
| 117 | I was listening to a song, which made me cry, but in a good way. | Joy:0.3 | Joy:0.3 | Joy:0.5 | Sadness:0.7 |
| 118 | I took the camera and got some nifty nature pictures. | Joy:0.5 | Joy:0.1 | Joy:0.7 | Joy:0.4 |
| 119 | i punched my car radio, and my knuckles is now bleeding | Sadness:0.9 | Sadness:0.3 | Anger:0.8 | Sadness:0.2 |
| 120 | I would feel guiltier if I were capable of caring more. | Neutral:0.0 | Guilt:0.3 | Guilt:0.4 | Neutral:0.0 |
| 121 | I need something more different and exciting. | Neutral:0.0 | Neutral:0.0 | Interest:0.5 | Neutral:0.0 |
| 122 | i hate crying, it makes me feel so vulnerable. | Disgust:1.0 | Disgust:1.0 | Disgust:1.0 | Disgust:0.9 |
| 123 | He always pursues revolutionary reactions | Neutral:0.0 | Neutral:0.0 | Interest:0.6 | Neutral:0.0 |
| 124 | I am weak, completely weak. | Sadness:0.4 | Sadness:0.2 | Sadness:1.0 | Sadness:0.1 |
| 125 | if you miss the meeting, I will hunt you down and brutally murder you :) | Joy:0.4 | Joy:0.4 | Surprise:0.3 | Joy:0.6 |
| 126 | the past few days I’ve been in really good moods | Joy:0.6 | Joy:0.1 | Joy:0.8 | Joy:0.48 |
| 127 | Don’t keep secrets, all it results in is people getting hurt. | Sadness:0.1 | Neutral:0.0 | Disgust:0.3 | Sadness:0.72 |
| 128 | sorry to whoever i may have upset. | Guilt:0.7 | Guilt:0.3 | Guilt:1.0 | Guilt:0.4 |
| 129 | I appreciate it, and respect it as a great album. | Joy:0.5 | Joy:0.1 | Interest:0.6 | Surprise:0.72 |
| 130 | I m [am] quite proud of my compositions. | Joy:0.7 | Joy:0.4 | Interest:1.0 | Joy:0.6 |
| 131 | I find myself secretly smiling at your posts | Joy:0.4 | Joy:0.2 | Shame:0.3 | Joy:0.48 |
| 132 | some girls were walking in front of us, they were ugly. | Disgust:0.7 | Disgust:0.7 | Disgust:0.7 | Disgust:0.4 |
| 133 | the conversation ended on a bad note, and it felt like she just ignored me | Sadness:0.7 | Sadness:0.2 | Sadness:0.7 | Sadness:0.32 |
| 134 | She see things very negatively, and her humor is very negative, but very funny. | Joy:0.3 | Joy:0.3 | Interest:0.4 | Sadness:0.11 |
| 135 | I’m going to enjoy getting to know all possibilities. | Joy:0.5 | Joy:0.1 | Joy:1.0 | Joy:0.6 |
| 136 | I’ve been talking to my older daughter again by email, but it is mostly hostile. | Sadness:0.6 | Anger:0.2 | Sadness:1.0 | Anger:0.48 |
| 137 | I have taken the exams timetable already :S | Fear:0.4 | Fear:0.2 | Surprise:0.5 | Fear:0.4 |
| 138 | It’s pitiful to see my cat trying to hop up on a window sill and falling off. | Sadness:0.6 | Sadness:0.3 | Sadness:0.8 | Sadness:0.3 |
| 139 | We were so pleased to know that yesterday’s boycott | Joy:0.7 | Joy:0.3 | Joy:0.9 | Joy:0.76 |

| | | | | | |
|---|---|---|---|---|---|
| | and related festivities proved to be peaceful. | | | | |
| 140 | I'm afraid I'll be forced to make a decision i don't want to make. | Fear:0.7 | Fear:0.7 | Fear:0.8 | Fear:0.8 |
| 141 | Charles was so impressed with our mad cleaning skills. | Surprise:0.9 | Surprise:0.8 | Surprise:0.9 | Surprise:0.76 |
| 142 | I use the ability to breathe without guilt or worry. | Neutral:0.0 | Neutral:0.0 | Neutral:0.0 | Neutral:0.0 |
| 143 | I cleaned the whole kitchen, and then blamed my boyfriend for making the mess. | Anger:0.4 | Anger:0.5 | Anger:0.7 | Sadness:0.24 |
| 144 | kill me please. | Sadness:0.8 | Guilt:0.4 | Guilt:1.0 | Fear:0.5 |
| 145 | what i am doing is horrible for my body. | Fear:1.0 | Fear:0.4 | Guilt:1.0 | Fear:1.0 |
| 146 | The Festival of Books was fabulous. | Surprise:1.0 | Surprise:0.6 | Joy:1.0 | Surprise:0.4 |
| 147 | he called apologizing and claiming that he had overslept. | Neutral:0.0 | Guilt:0.6 | Shame:0.6 | Guilt:0.4 |
| 148 | the one guy told so comfortably to me as if we were friends for life. | Joy:0.4 | Joy:0.2 | Surprise:0.9 | Joy:0.15 |
| 149 | I find this name utterly ridiculous, sexually suggestive, and repulsive. | Disgust:1.0 | Disgust:0.8 | Disgust:1.0 | Disgust:0.8 |
| 150 | Despite many failed maneuvers, I like to dance! | Joy:0.7 | Joy:0.4 | Joy:0.7 | Joy:0.6 |
| 151 | i have never felt more stupid than i did today in my thesis defense. | Shame:1.0 | Shame:0.8 | Anger:0.9 | Neutral:0.0 |
| 152 | I haven't seen a cookbook that really excites me lately. | Neutral:0.0 | Sadness:0.1 | Sadness:0.5 | Neutral:0.0 |
| 153 | i hate the way people look at me when i cry. | Disgust:1.0 | Disgust:1.0 | Disgust:0.9 | Disgust:0.9 |
| 154 | Stephs is eating Spaghetti, and it smells sooo good. | Joy:0.6 | Joy:0.2 | Interest:0.9 | Joy:0.24 |
| 155 | i was so tired, but it was a nice day nonetheless. | Joy:0.5 | Joy:0.2 | Joy:0.7 | Joy:0.16 |
| 156 | i think my hair is growing longer :D | Joy:1.0 | Joy:0.6 | Joy:0.5 | Joy:0.8 |
| 157 | I saw this movie without interest | Neutral:0.0 | Neutral:0.0 | Disgust:0.8 | Neutral:0.0 |
| 158 | Canada is a rich country, but still it has many poor people. | Sadness:0.2 | Sadness:0.3 | Shame:0.5 | Sadness:0.56 |
| 159 | Oh no, I forgot that the exam was today! | Sadness:0.6 | Sadness:0.6 | Surprise:1.0 | Sadness:0.6 |
| 160 | I hurt people unintentionally. | Guilt:0.7 | Guilt:0.5 | Shame:1.0 | Sadness:0.72 |

* AAM – Affect Analysis Model

** PAQ – Posing a question

# Appendix C: Instruction and Questionnaire for User Study on AffectIM

## INSTRUCTION

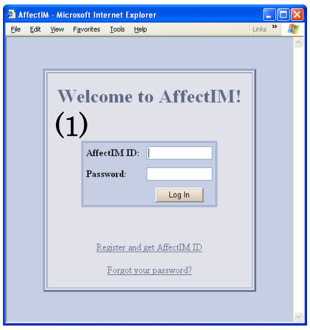
**We would kindly ask you to read this page carefully before we start the experiment**

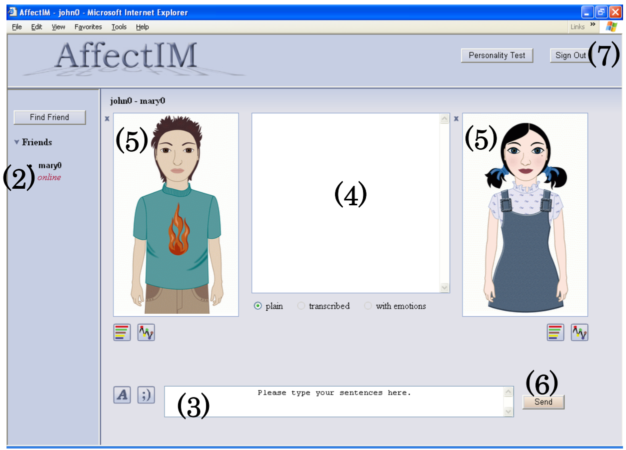
In this study, we want to evaluate a new kind of Instant Messaging (IM) system.

1. At the beginning of the study you will be given the questionnaire with your AffectIM ID at the top of the first page.

2. The experiment consists of three sessions, and each session lasts approximately 8-10 minutes. During the session, you will be asked to communicate with your online interlocutor via interface of AffectIM system.

3. Before each session, experimenter will open particular interface. The topic of the conversation will be given to you at the beginning of each session. Please read it carefully. Then (see corresponding numbers on the Figure below):
   (1) please login to the system using your AffectIM ID and the same password
   (2) when the main window opens, you will see the name of your conversation partner in the left side. Please, double-click on his/her name, when you notice that he/she is "*online*"
   (3) please type your dialog in the input field. Since the time for the session is short, we kindly ask you to support the conversation flow continuously, and feel free to show emotions in your dialog
   (4) the conversation flow will be displayed in the text field
   (5) the avatar to the left will represent you, and the avatar to the right – your partner




4. In order to keep your attention on the conversation, we intentionally disabled some functionality of the AffectIM interfaces. Therefore, please, do not try to push buttons on the screen, except button (6) "Send" and "select menu" (in the interface which allows manual selection of emotion and its intensity).

5. Female user is supposed to start the conversation. When the time for the session runs out, experimenter will ask you to finish the dialog by typing "bye-bye". Then, please "Sign Out" (push button (7)).

6. After each session, please fill in corresponding page of the questionnaire. At that time, the experimenter will prepare the next interface.

7. After you finish all the sessions, please complete the questionnaire.

**Thank you for participating in our study!**

**AffectIM_ID:________________**

## QUESTIONNAIRE

**SESSION: _________________**

**1. The system was interactive.**

| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
|---|---|---|---|---|---|---|
| Strongly disagree | Disagree | Weakly disagree | Don't know | Weakly agree | Agree | Strongly agree |

**2. I felt it was important for my conversation partner that I responded after each his/her statement.**

| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
|---|---|---|---|---|---|---|
| Strongly disagree | Disagree | Weakly disagree | Don't know | Weakly agree | Agree | Strongly agree |

**3. I was awaiting the replies of my conversation partner with true interest.**

| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
|---|---|---|---|---|---|---|
| Strongly disagree | Disagree | Weakly disagree | Don't know | Weakly agree | Agree | Strongly agree |

**4. I felt if I were communicating with my conversation partner in the shared virtual space.**

| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
|---|---|---|---|---|---|---|
| Strongly disagree | Disagree | Weakly disagree | Don't know | Weakly agree | Agree | Strongly agree |

**5. The system gave me the sense that the physical gap between us was narrowed.**

| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
|---|---|---|---|---|---|---|
| Strongly disagree | Disagree | Weakly disagree | Don't know | Weakly agree | Agree | Strongly agree |

**6. I enjoyed the communication using this IM system.**

| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
|---|---|---|---|---|---|---|
| Strongly disagree | Disagree | Weakly disagree | Don't know | Weakly agree | Agree | Strongly agree |

**7. The system was successful at conveying my feelings.**

| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
|---|---|---|---|---|---|---|
| Strongly disagree | Disagree | Weakly disagree | Don't know | Weakly agree | Agree | Strongly agree |

**8. The system was successful at conveying my partner's feelings.**

| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
|---|---|---|---|---|---|---|
| Strongly disagree | Disagree | Weakly disagree | Don't know | Weakly agree | Agree | Strongly agree |

**9. The emotional behavior of the avatars was appropriate.**

| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
|---|---|---|---|---|---|---|
| Strongly disagree | Disagree | Weakly disagree | Don't know | Weakly agree | Agree | Strongly agree |

**10. I understood the emotions of my communication partner.**

| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
|---|---|---|---|---|---|---|
| Strongly disagree | Disagree | Weakly disagree | Don't know | Weakly agree | Agree | Strongly agree |

**11. I am satisfied with the experience of communicating via this system.**

| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
|---|---|---|---|---|---|---|
| Strongly disagree | Disagree | Weakly disagree | Don't know | Weakly agree | Agree | Strongly agree |

## GENERAL QUESTIONS:

**1. Please associate nine emotion states with the avatar expressions (write corresponding number in □). If you are confident, please write only one number in first □, if not, please indicate two variants:**

1. Anger
2. Disgust
3. Fear
4. Guilt
5. Interest
6. Joy
7. Sadness
8. Shame
9. Surprise

**2. Had you used a computer based chat system or Instant Messenger before?** ☐ Yes ☐ No

**3. While online, do you use emoticons or abbreviations?** ☐ Yes ☐ No

**4. How often do you make spelling mistakes because of fast typing?**

| ☐ | ☐ | ☐ | ☐ | ☐ |
|---|---|---|---|---|
| Never | Rarely | Sometimes | Often | Always |

**5. To what degree do you think is necessary to look at a graphical representation of the other communicating person?**

| ☐ | ☐ | ☐ | ☐ | ☐ |
|---|---|---|---|---|
| Never | Rarely | Sometimes | Often | Always |

**Why?**

**6. Do you consider the manual selections of emotion state and intensity were helpful?** ☐ Yes ☐ No

**Why?**

**How often did you use this function, when you wanted?**

| ☐ | ☐ | ☐ | ☐ | ☐ |
|---|---|---|---|---|
| Never | Rarely | Sometimes | Often | Always |

**7. Please describe the general impression about the AffectIM system.**

**Thank you very much!**

# Publications

**International Conference proceedings with full paper review:**

Neviarouskaya A., Prendinger H., and Ishizuka M. An Expressive Avatar for Instant Messaging Endowed with Emotional Intelligence (Poster paper). In: *Proceedings of 7th International Conference on Intelligent Virtual Agents (IVA'07)*, Springer LNCS, Paris, France, Sept. 2007, pp 395-396

Neviarouskaya A., Prendinger H., and Ishizuka M. Textual Affect Sensing for Sociable and Expressive Online Communication. In: *Proceedings of 2nd International Conference on Affective Computing and Intelligent Interaction (ACII'07)*, Springer LNCS, Lisbon, Portugal, Sept. 2007, pp 220-231

Neviarouskaya A., Prendinger H., and Ishizuka M. Recognition of Affect Conveyed by Text Messaging in Online Communication. In: *Proceedings of 2nd International Conference on Online Communities and Social Computing (OCSC'07)*, held as part of HCI International 2007, Springer LNCS 4564, Beijing, China, July 2007, pp 141-150

Neviarouskaya A., Prendinger H., and Ishizuka M. Narrowing the Social Gap among People Involved in Global Dialog: Automatic Emotion Detection in Blog Posts (Poster paper). In: *Proceedings of International Conference on Weblogs and Social Media (ICWSM'07)*, Omnipress, Boulder, Colorado, USA, March 2007, pp 293-294

Neviarouskaya A., Prendinger H., and Ishizuka M. Analysis of Affect Expressed through the Evolving Language of Online Communication (Short paper). In: *Proceedings of International Conference on Intelligent User Interfaces (IUI'07)*, ACM Press, Hawaii, USA, Jan. 2007, pp 278-281

**Conference proceedings without review:**

Neviarouskaya A., Prendinger H., and Ishizuka M. Towards Expressive Online Communication: Textual Affect Sensing and Visualization. In: *Proceedings of 69th National Conference of Information Processing Society of Japan*, Vol. 4, Tokyo, Japan, March 2007, pp 237-238