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Affective computing and affective learning – methods, tools and prospects

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Abstract: Every teacher knows that interest, active participation and motivation are important factors in the learning process. At the same time e-learning environments almost always address only the cognitive aspects of education. This paper provides a brief review of methods used for affect recognition, representation and processing as well as investigates how these methods may be used to address affective aspect of e-education. The paper analyzes on how affective learning and affective computing can be combined to assess and improve effectiveness of educational processes, including the processes enhanced with technology. Three case studies are analyzed to illustrate the complexity and diversity of affective learning tools. Some of the challenges of affective computing are outlined and prospects of application in e-learning are discussed.

Słowa kluczowe: affective computing, affect recognition, affective learning, intelligent tutoring systems

1. Introduction

Whether we like it or not, we, human beings, are emotional and we treat all of the surrounding entities and events emotionally. We also react emotionally in interaction with computers, which are commonly considered as purely logical and mechanic. But even if virtual worlds, characters and events are artificial, human emotions in reaction to them are not artificial, but real. In some computer application domains, emotionality of users may influence the effectiveness of the tasks performed. One of the domains where emotions may play a crucial role, is an e-learning. There is lots of evidence that some emotional states support the learning processes and others suppress them (Picard, 2003; Sheng, Zhu-ying & Wan-xin, 2010; Hudlicka, 2003). The distinction between the two groups of emotional states in some cases is not obvious, for example such a positive mood as hilarity is not good for learning processes, while slightly negative emotional states foster critical thinking and are appropriate for analytical tasks.

In a traditional classroom affective issues such as fatigue, lack of concentration, low motivation or boredom can be noticed by teachers, and though their actions may include long-term tactics, such as difficulty gradation or task individualization, but sometimes simple words of encouragement or appraisal work as well (Landowska, 2013). In e-learning environments, in asynchronous model of education, a learner is sometimes left alone with educational resources and underlying software. In this case one may fail to deal with fluctuation in motivation and concentration and follow the feelings of boredom or frustration (and more). As a result effectiveness of the education may be reduced or the learning process may be paused or even abandoned. Some virtual universities reported a large problem of the resignation rate before course completion (up to 70% of courses were paused or abandoned) and the problems were addressed by human mentoring on-line (Landowska, 2008).

Human mentors report to devote at least as much time and attention to emotional goals in tutoring as they do to achieve the cognitive goals (Picard, Papert, Bender, Blumberg, Breazeal, Cavallo, Machover, Resnick, Roy & Strohecker, 2004). At the same time, Intelligent Tutoring

Systems (ITS) and other e-learning environments almost always address only the cognitive goals (Picard et al., 2004; Anderson, Boyle, Corbett & Lewis, 1990). Nobody denies that interest, active participation and motivation are important factors in the learning process (Picard et al., 2004) and therefore the enhancement of ITS with affect-related mechanisms may improve the effectiveness of technology-supported learning.

This paper tries to explore how affective computing methods and tools can be used in e-learning environments in order to support educational processes. First, a review of affective computing methods used for recognition, representation and interpretation of human emotional states is presented. It was not possible to describe, or even to mention, all of the available affective computing solutions, therefore the article focuses on the ones that are important for possible applications in e-learning tools. Then, a brief summary of findings in affective learning is provided to name the role of emotions in educational processes. To illustrate complexities and difficulties of affective computing methods applied in e-learning, three case studies of intelligent tutoring systems are described. Case studies analysis allows to draw some conclusions on challenges and prospects of affective computing in the service of technology-enhanced learning.

2. Affective computing

Affective computing is a relatively new research domain defined in 1995 as computing that relates to, arises from, or deliberately influences emotion or other affective phenomena (Picard, 1995). It is a part of human-computer interaction research which focuses on creating systems that take into account users' emotional states. It comprises three subdomains: affect representation and recognition, affect interpretation and modeling as well as affect simulation. Although affective computing has developed some tools and methods since 1995, there is still much room for progress and new ideas, and research reveals more questions than answers, which is typical for young scientific domains.

2.1. Systems that deal with emotions

Applications that can be described as an affect-related and benefit from affective computing methods can be very diverse: affect-based games, diagnosis tools, affective tutoring systems, emotion monitors or personality simulators for virtual characters, to name just a few. Systems that deal with emotions can be divided into two subgroups that differ on the human-computer interaction level distinguishing one-way or two-way communication.

One-way communication occurs when there is no loop-back that follows information on affect. Observations or simulations are made, but there is no system reaction that follows. Two-way affective communication occurs when information on affect is followed by the reaction to it and there is a cycle of affective communication in human-system interaction. A family of affect-related systems is provided in Figure 1.

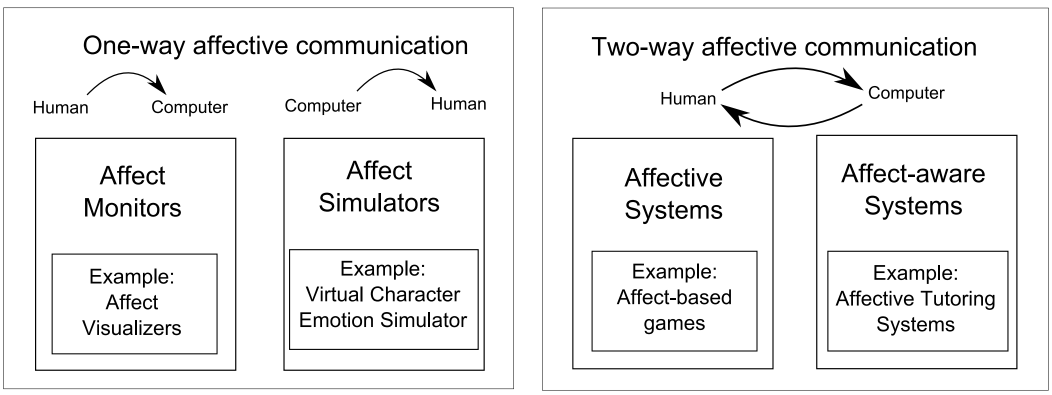

Figure 1. Family of affect-related systems

One-way affective communication systems can be therefore divided into affect monitors and affect simulators. An affect monitor is a system that automatically recognizes human affect and that information is stored and/or displayed, however there is no system reaction (application does not change its behavior) to any affective state of a user, therefore only one-way communication occurs. An example of affect monitor is an emotion graphic visualizer that recognizes emotional state and visualizes it using different display controls (Landowska, 2012c). Another example is a graphical representation of an affect (mood) recognized from textual analysis of poems (Kradinac, 2008). Affect simulator is a software that does not take any input channel from user observations, but generates affective states based on some predefined conditions. Simulators can model how human emotions are evoked, but also can be used for affect modeling of virtual characters. Virtual characters' emotion simulators take into account definitions of personality, mood and reactions to stimuli to produce consistent and consequent character behavior (Landowska, 2012b).

Two-way human-computer affective interaction occurs when a system recognizes and adapts its control flows to user emotional state. Within that category another distinction could be made for affective and affect-aware applications.

Affective software is a system that is designed for emotional interaction and its main objective is to influence emotional states of a user. Examples of affective applications include affect-based adaptive games or chatterbots changing the conversation depending on a user's affective state.

An affect-aware system can be defined as a program of any main functionality that additionally recognizes emotional state of a user and contains control mechanisms and application logic able to handle the information on affect (Landowska, 2013). The main function of the affect-aware applications is performing effectively predefined tasks, like monitoring or problem solving, but they additionally take information on user's affect into consideration. Affective intervention is a modification of standard control path or system behavior that is a response to user affective state and aims at providing effective execution of a task. The affect-aware systems could and should make an intervention when certain objectives (i.e. task effectiveness) are not met, however the system should not make an intervention, while it would disturb the user to do appropriate tasks. A typical example of affect-aware application is an adaptive tutoring system that changes learning path when it recognizes user's ineffective emotional state (for example boredom), but refrains from interventions when emotional state is considered neutral or effective for the task performed.

The distinction between affective and affect-aware applications is important for setting the objective of user's emotion recognition component. In the first case of affective systems, any occurrence of some symptoms of emotions should be interpreted as an existing affective state of the user. In affect-aware systems the hypothesis on emotional state should be done with precaution as an unnecessary application intervention would be very disturbing and may decrease effectiveness of task execution. To make the distinction more precise, let's consider the automatic emotion recognition as testing hypothesis 'user affective state requires intervention' against null hypothesis 'user affective state does not require intervention' (Landowska, 2013). The affective software should minimize type II error (existing emotional state was not recognized and addressed), while affect-aware systems should minimize type I error (non-existing emotional state was recognized and system makes unnecessary intervention).

2.2. Emotion recognition in affect-related applications

One of the most important components of affect-related systems (except for affect simulators) is emotion recognition algorithm. There are numerous emotion recognition algorithms which differ in input information channels, output labels or representation models and classification methods. From the perspective of application in human-system interaction, the most important classification is based on input channel, as not all the channels are available in the target environment.

One can distinguish:

- algorithms based on visual information processing (Binali, Wu & Potdar, 2009; Zeng, Pantic, Roisman & Huang, 2009; Bailenson, Pontikakis, Mauss, Gross, Jabon, Hutcherson, Nass & John, 2008),
- algorithms based on body movements analysis (Zeng et al., 2009; Boehner, DePaula, Dourish & Sengers, 2007),
- algorithms based on text analysis (Liu, Lieberman & Selker, 2003; Neviarouskaya, Prendinger & Ishizuka, 2009; Binali, Wu & Potdar, 2010; Ling, Bali & Salam, 2006; Li & Ren, 2008),
- algorithms based on voice signals processing (Zeng et al., 2009; Picard & Daily, 2005),
- algorithms based on usage patterns of standard input devices (Kołakowska, 2013),
- algorithms based on physiological measurements interpretation (Picard & Daily, 2005; Szwoch, 2013; Bailenson et al., 2008).

A video input is the most commonly used channel for emotions' recognition, as it is a universal and not disturbing method of user monitoring. Algorithms analyze face muscle movements, body posture changes and gesticulation in order to assess user's emotional state, however the algorithms are sensitive to changes in lighting and uneven illumination. Body movement analysis can be performed on video input, but also by using specialized equipment such as a pressure matte placed on a chair. As special equipment is rarely available in educational environments (both in class meeting or at home desk in e-learning), video analysis is a better option for technology-enhanced learning, providing that a video image is of enough quality and lighting in the room is sufficient for recognition purposes.

Affect recognition from analysis of text is often used for a public opinion mining. There are several examples of retrieving attitudes towards politics or certain topics from analysis of blogs, forums or chats. If an e-learning environment is text-based (conversation-based), the text analysis is sufficient for recognizing learners' emotional state (Landowska, 2013). For other types of educational tools (not based on conversation), a more promising approach is the analysis of peripheral device usage patterns. There are studies on affect retrieval from changes of keyboard stroke patterns and mouse movement patterns (Kołakowska, 2013).

Changes in voice and intonation are also one of the well recognized symptoms of emotional states, however voice communication would be required for application in e-learning environment. Physiological measurements, although very precise and proved to be good predictors of emotional states (Szwoch, 2013), require specialized equipment also rarely available in educational environments.

Although there are so many algorithms, they differ significantly in the number of input channels, number of features and methods of data extraction, feature selection and classification process. Classifiers are usually built on one of the known artificial intelligence tools, including decision trees, neural networks, Bayesian networks, linear discriminant analysis, linear logistic regression, Support Vector Machine, Hidden Markov Models (Kołakowska, Landowska, Szwoch, Szwoch & Wrobel, 2013). Depending on the classification method, input channels and selected features, accuracy of affect recognition differs significantly, rarely achieving up to 98 percent. It is important to emphasise that highest accuracies are obtained mainly for two-class classifiers and multimodal input channels (including biomeasurements).

From the perspective of application of affect recognition method in e-education two major qualifiers must be taken into account: granularity of emotion recognition and input channels that are required by an algorithm.

Granularity of emotion recognition can be defined as a level of detail considered in emotion recognition process and can be measured with the number of distinguishable emotional state classes that can be provided as an algorithm's output. Two-class recognition of affect might be not sufficient for e-learning purposes, as differentiating only positive and negative emotions, or stress and lack-of-stress, which are not an adequate granularity level for majority of tutoring systems.

For e-education most sufficient input channels include the ones available at home computer desk, such as: video (not always available), peripheral devices usage, text inputs. Those input channels should be used in a combination to improve accuracy of affective state recognition. Known algorithms are based on different emotional state representation models, making their outputs incomparable with other algorithm findings and their combination and application difficult. In order to compare and combine results of different recognition algorithms the output should be expressed with the same affect representation model or the appropriate model mapping should be provided.

2.3. Affect representation for computers

Once recognized, emotions must be represented in some way in order to be interpreted by computer systems or to be presented to a program user. There are four major model types of emotional state representation: discrete, dimensional, componential and label-based. Discrete models distinguish a set of basic emotions and describe each affective state as a combination of the basic ones. The most important model in this category is Ekman six basic emotion model including: joy, sadness, fear, surprise, anger and disgust with emotional state expressed as a combination of these already mentioned (Ekman & Davidson, 1999). Some emotional states are hard to represent in that model, for example boredom. Ekman proposed also a set of 7 basic emotional states and a set of 21 states. It is important to emphasise, that Ekman did not propose the emotion sets as an affect representation model, but he rather investigated basic emotions that are common for all humans, independently of their culture and origin. However, some of the emotion recognition algorithms use the Ekman's basic six ones as their output, some use just a subset of four, some use seven and emotional states are sometimes represented as a combination of basic emotions (secondary or tertiary emotional states).

Other recognition algorithms use dimensional models that represent the emotional state as a point in a two or three-dimensional space. The two-dimensional scale known as Whissel wheel includes valence (positive versus negative attitude) and arousal (high or low stimulation) (Whissell, 2009). The third dimension proposed by Russell and Mehrabian – dominance represents 'fight or escape' reaction to stimuli resulting in PAD emotional space (Mehrabian, 1997). In dimensional models a specific affective state is represented as a point, with dimensional values ranging from -1 to 1 (sometimes -10 up to 10 or -100 up to 100 scales are used). Points with coordinates close to zero are considered neutral. An example PAD visualization with exemplary emotions location is provided at Figure 2. The emotional state 'angry' can be represented as a point (-0.51, 0.59, 0.25). In Figure 2 letter size of textual labels corresponds to dominance dimension coordinate (positive dominance labels are bigger).

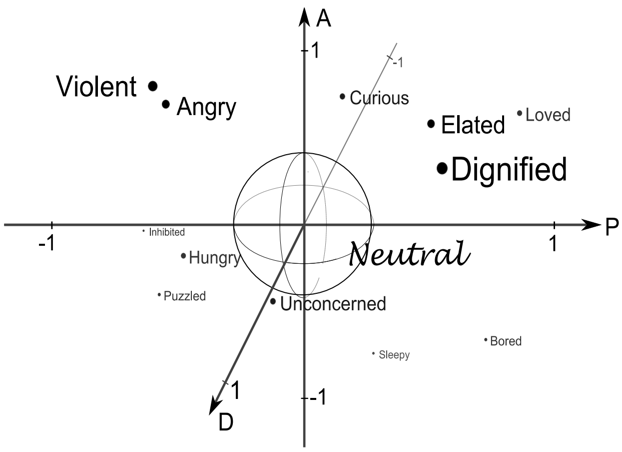

Figure 2. PAD emotion representation model (adapted from (Mehrabian, 1997))

Dimensional models are easy to process and interpret by computer systems and their mathematical representation is used in emotion analysis and synthesis for simulation purposes.

A significant group of emotion recognition algorithms use emotion representation based on labels where distinguished affective states are assigned with words, for example: boredom, joy, flow. That type of representation model is more intuitive for humans but less sufficient for computer processing. Labels determine distinguishable emotional states and in most of the studies assumed sets of labels are different. That kind of representation causes serious interpretation problems due to fuzziness of linking concepts with words and a problem of semantic disambiguation.

The composite models combine discrete or dimensional scales with labels to express emotion gradation.

There is a major problem of uncertainty and fuzziness of concepts related to human emotions. Categories and terms describing affective states that are used by humans are imprecise and can be interpreted in multiple ways. Labels are specifically misleading – a definition of 'angry' may differ significantly in individual interpretation meaning that in particular some people will assign it to a point distant from average (-0.51, 0.59, 0.25). For computer systems a difference between 0.546 and 0.547 is distinguishable, while human assessment of emotions is not so precise. In the representation of emotional states fuzziness and uncertainty must be taken into account.

Practical implications for affective computing application in technology-enhanced learning include the following: one common representation model must be used for affect recognition and interpretation, fuzziness of affective states should be also expressed and interpreted and there is a need for an explicit definition of a distinguishable set of affective states that are under investigation for a specific tool or task.

2.4. Affect interpretation and analysis

Emotional state of a user that was recognized and represented, for example as a label or a point in PAD scale, is a subject for further analysis. The interpretation of emotional state should take into consideration the context of occurrence, especially preceding events and triggers, as well as individual characteristics of a subject. In other words the emotional state of a person depends not only on stimuli, but may also depend on: personality, previous experience, daily mood or even current weather.

The human-computer interaction in the two-way communication model that takes into account information on user's emotional states can be considered as a constant loop of user's observation, affect recognition, interpretation and affective intervention as it is shown at Figure 3. Affect interpretation has an overall purpose in determining whether affective intervention is required. A short loop that skips affective intervention would be frequently a chosen flow path, as not all emotional states of a user would require system reaction. A long loop should be taken into account only if an affect-aware system identifies an emotional state that is inadequate for effective work.

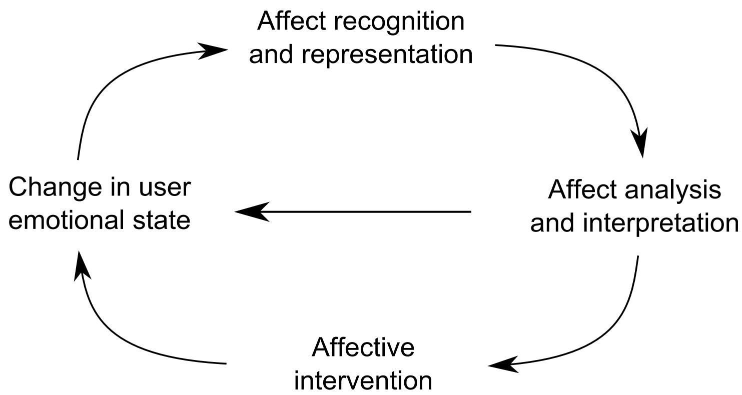

Figure 3. Affective human-computer interaction loop

Affect symptoms observations and recognition should be made constantly and independently on user's activity with system interface. Practically affect analysis should be performed when there is a significant change in observation data. The definition and identification of inadequate emotional states that require intervention should be context-based and might be different for working, gaming or learning tools. Affect-aware systems' actions would be triggered either by user events or recognized user emotional states that require intervention.

3. Affective learning

Affective learning is a term used to describe the phenomena of emotional states' influence on human cognition and learning and it had been explored in psychology and pedagogy a long time before affective computing developed its methods and tools. Before presenting the combination of affective learning and affective computing, a brief summary of affective learning findings should be provided to name the role of emotions in education.

Literature analysis allows to distinguish several general rules of affect influence on learning processes:

- emotional states of a very high or very low arousal (both positive and negative valence) disturb learning processes (Elliott, Rickel & Lester, 1999),
- emotional states with a high arousal (both positive and negative) foster remembrance of facts,
- educational processes are supported by the states of engagement, concentration and flow (Picard & Klein, 2002; Baker, 2007),
- different emotional states support different learning tasks (Kapoor, Mota & Picard, 2001),
- slightly negative states are better than positive ones (as negative states foster critical and analytical thinking) (Baker, 2007; Ben Ammar, Neji, Alimi & Gouardères, 2010),
- emotional states with a higher dominance factor support learning process (moderate anger is better than fear in the educational environment) (Ben Ammar et al., 2010; Hone, 2006).

Affective computing methods and tools are used nowadays to support and explore affective learning phenomena. For example, research conducted on a large international group of novice students (730) in Netherlands has indicated that achievement emotions play as an important mediator in how students engage with on-line and face-to-face education (Tempelaar, Niculescu, Rienties, Giesbers & Gijselaers, 2012). Another study on educational virtual world (Second Life) measured the students' level of enjoyment and boredom and its influence on students' achievement level (Noteborn, Bohle Carbonell, Dailey-Hebert & Gijselaers, 2012).

In distance learning affective aspects are even more important and might be the critical factor of successful education. It is important to differentiate synchronous and asynchronous learning environments, however for both the affective aspect can be considered. In synchronous learning a teacher and learners meet in virtual space, and that allows the teacher to address most of the motivational issues. However, the teacher may fail to recognize unproductive emotional states like boredom or frustration, as the learner's observation possibilities are limited. Sometimes the teacher tracks only the learner's activities within the application and there is no video input from the learner's home. If the learner does not report motivational problems to the teacher (part of students would not), the teacher may be unable to foster the learner's concentration and attention.

In asynchronous learning the learner performs educational tasks on his own, and any affect-related problems cannot directly be noticed and addressed by the teacher. Fluctuation in motivation and concentration is one of the issues the learner must deal with. The success in asynchronous learning processes depends significantly on the learner's self-discipline. Recent research on the motivation of a learner emphases also the role and importance of a complex interaction with his/her peers in the online community (Rienties, Giesbers, Tempelaar, Lygo-Baker, Segers & Gijselaers, 2012).

From this perspective it would be postulated to support affective aspects of learning in distance and electronic educational environments, applying some of the methods and tools that are developed by affective computing domain.

4. Combination of affective learning and affective computing

An idea of combination of affective learning and affective computing is not a new one, as affective computing researchers often apply their methods in learning process analysis. Moreover, lots of methodological and didactic findings are achieved by the means of technology-enhanced learning monitoring. The unquestionable achievement of affective computing is the research on the states of frustration and flow, as well as research on emotional states in different types of educational tasks (Noteborn et al., 2012; Ahn & Picard, 2006). However, the research usually focuses on one perspective or one emotional state only, for example only on frustration or only on boredom (Bessiere, Newhagen, Robinson & Shneiderman, 2006; Scheirer, Fernandez, Klein & Picard, 2002; Ang, Dhillon, Krupski, Shriberg & Stolcke, 2002). Woolf et al proposed a set of useful cognitive-affective terms scales for emotion labeling dedicated to learning processes. The states were additionally assigned numeric representation of desirability in educational processes (for example concentration was rated 2- 'highly desirable', while boredom was rated 0 – 'not desirable') (Woolf, Burleson, Arroyo, Dragon, Cooper & Picard, 2009). Some educational tasks are also better investigated than others (Calvo & D'Mello, 2010).

In 2004 a group of affective computing researchers proclaimed affective learning manifesto (Picard et al., 2004) that identified main gaps in methods and tools for affective learning, including:

- the extension of cognitive theory to explain and exploit the role of affect in learning,
- incompatibility of emotion theories with computer-based processing,
- reliable measurements of emotional states symptoms,
- objective interpretation of affective phenomena
- embodied agent influence on user affect.

In 2013, nine years later, most of the problems identified remain open and research reveals sometimes more questions than answers (Landowska, 2013). However, there are some examples of successful application of affective computing methods and tools in analyzing impact of affect in technology-enhanced education (Baylor, 2011; Moreno & Mayer, 2007; Rovai, Wighting, Baker & Grooms, 2009). There are also some examples of affect-aware tutoring systems that address the issue of students' emotional states recognition and elicitation (Landowska, 2013; Alexander, Sarrafzadeh & Hill, 2006; Sarrafzadeh, Alexander, Dadgostar, Fan & Bigdeli, 2008; Van Mulken, André & Müller, 1998; Landowska, 2012a; Abou-Jaoude, Frasson, Charra & Troncy, 1999). In that context affect–awareness of a tutoring system can be defined as: the system being aware of the emotional state of a learner and being able to make intervention, when learning process is endangered (and only then) (Landowska, 2013). Sarrafzadeh et all (Alexander et al., 2006) proposed a term of Affective Tutoring Systems, however that term is not commonly used yet.

To illustrate the diversity of the affective computing methods applied in e-learning, three case studies of intelligent tutoring systems were chosen and described: Eve, Gerda and Duffy. Eve has a very sophisticated avatar and uses body language communication, including expression of emotions by a virtual tutor; Gerda is a dialogue-based system and analyzes student affective state to make affective interventions in conversation, while Duffy has a relatively simple static interface, however its actions are aimed at increasing learner's motivation and engagement. All of the described tutoring systems can be perceived as affect-aware applications, although they significantly differ in interaction model, user interface and internal design of affect handling.

4.1. Affective tutor Eve

Easy with Eve is an affect-aware tutoring system which is capable of detecting and expressing affect while teaching mathematics and it uses embodied tutor Eve for communication with students (Alexander et al., 2006). A student's affect in the system is detected with a real time facial expression analysis algorithm that detects six basic Ekman emotional face expressions with a support of a vector machine classifier (Sarrafzadeh et al., 2008).

An intervention model in Eve is based on detailed study of human tutors responding to student affective states. An experiment was carried out basing on traced patterns of interactions between human teachers and their student in one-to-one sessions. The interaction patterns that followed affective states of a learner were extracted from a video track analysis. The knowledge on interaction templates was then used to create sets of recommended actions to be undertaken by a virtual tutor Eve. Each recommended intervention was provided with a measure of suitability for the situation and Eve had chosen an action with the probability that was equivalent to the measure.

Affective interventions included a consistent Eve's reaction that coordinated facial expressions, words and gestures. The avatar of Eve is able to display a comprehensive range of different behaviors, including symptoms of emotions. Examples of neutral, smiling and pointing while speaking poses is provided in Figure 4.

Figure 4. Affective tutor Eve (Alexander et al., 2006)

Easy with Eve tutoring system was developed at Massey University in New Zealand and was used to help primary school students with numeracy exercises. It is designed to exploit persona effect, which means that the presence of a lifelike character can strongly influence students to perceive their learning experiences positively. The persona effect has been shown to increase learner's motivation, especially in technical domains (Van Mulken et al., 1998).

4.2. Conversation-based tutor Gerda

Gerda bot is a prototype of a conversational Intelligent Tutoring System developed under supervision of the paper's author at Gdansk University of Technology. Gerda questions students on operating systems and uses a metaphor of student-teacher conversation during an oral examination. Gerda can be classified as an authoritative teacher (Landowska, 2008). A question-answer dialogue is performed using keyboard input (a voice channel is not used). Gerda dialogue is driven by a lesson scenario that is divided to topics, questions and concepts. Gerda uses a set of pedagogical strategies to help students in answering questions correctly: hinting, prompting and testing. Gerda is also capable to answer simple predefined questions asked by students. Gerda evaluates the student's answers based on the list of concepts that are assigned to each question. If an answer is incomplete Gerda prompts a student for more detailed statements until all concepts are passed or there is no more hint to be used.

Gerda interface uses textual and visual communication. It is visualized with a set of video recordings of an actor and the videos sequenced on the run, depending on current conversation state. There are over sixty different video films that last for 20 up to 90 seconds and for sequencing purposes they start and end with the same neutral actor's pose. Scenes represent a range of behaviors, including some neutral, but also affective ones such as smiling or nodding. The only negative emotional state represented is a slight boredom that is represented by looking around. An example screenshot of Gerda conversation window is provided in Figure 5.

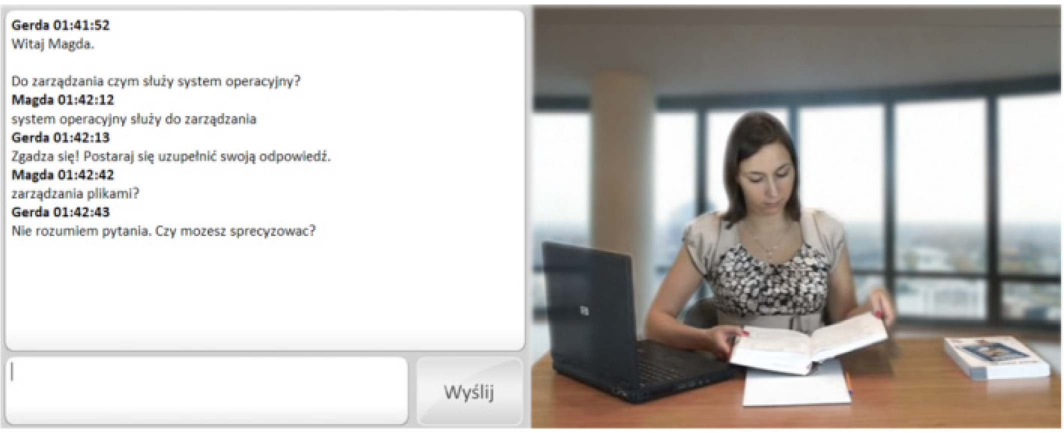

Figure 5. Affect-aware virtual tutor Gerda (Landowska, 2012a)

Affect-awareness mechanisms in Gerda can be described with the following characteristics:

- PAD emotional state was chosen as a student affect representation model,
- affect recognition was based on analysis of student's textual inputs,
- recognition algorithm used keyword-spotting technique based on affect-tagged dictionary and a set of heuristics,
- trustworthiness model was used to deal with fuzziness and uncertainty of emotion recognition,
- classification of student's emotional states into affect patterns (classes) was performed with minimal distance algorithm.

Additionally a set of affective interventions was proposed for anger, frustration, boredom, hilarity and idleness. For some emotional states there were multiple scenarios for different degrees of arousal and different certainty level. Neutral student's emotional states and states with low certainty level were not followed by an intervention – a thematic conversation scenario was continued instead.

Visual Gerda output was matched with textual prompts and responses, however lip's movement synchronization was not performed. Gerda's behaviour (a film to be added to display sequence) was chosen based on the conversation state and a student's emotional state.

During the design and implementation of this functionality some problems were encountered, including insufficient quality of emotion recognition from video input, lack of Polish dictionary of affect-tagged words and insufficient granularity of emotion recognition algorithms.

At the beginning there was a plan to combine affect elicitation from text analysis and video analysis. A set of existing libraries for emotion recognition from face muscle movements was analyzed, but proved to be very sensitive to lighting conditions. If lighting of a face was uneven or insufficient, algorithms tend to make large errors (recognition of anger while smiling). Only direct exposition of a face to windows, when lighting was even and good, improved accuracy of the emotion recognition.

Most of the other algorithms that were considered to be used, suffered from two main problems: provided insufficient granularity of an output and not provided any quality measure of the result.

Most of the emotion recognition algorithms provided only two-class classification of emotional state (for example boredom-no boredom) and moreover, it was expressed with labels only, causing problems with concept fuzziness. The outputs were then incomparable and most of them provided only information that a certain state is not recognized (no-boredom). The best granularity was provided by algorithms based on textual analysis, as some of them represented emotional state even with continuous scales (PAD model). However, another problem was encountered while implementing text-based emotion recognition – Gerda conversations with students are held in Polish and dictionaries of affect-tagged words were available only in English. Different translation methods were used, however the results were unsatisfactory.

Concluding, this practical attempt to build an affect-awareness mechanism for ITS showed that tools and methods in affective computing are not mature yet and still more research is required to provide quality and applicability of the results.

4.3. Troublemaking learning companion Duffy

A learning companion Duffy was created in Montreal University and uses a metaphor of co-learner to support educational processes (Abou-Jaoude et al., 1999). Duffy is not equipped with extensive domain knowledge, its main objective is to foster effective emotional states of a learner in two ways: as a learning companion Duffy creates a feeling of competition and it provides hints for a learner. The hints provided are sometimes correct and sometimes wrong, and therefore Duffy is also called a troublemaker. Wrong hints are intended to cause cognitive dissonance (a learner's answer vs. Duffy's answer) and a technique of creating and resolving cognitive dissonance can have a powerful impact on educational outcomes and learner's motivation (Chou, Chan & Lin, 2003). The interface of the application with Duffy character in the middle is shown at figure 6.

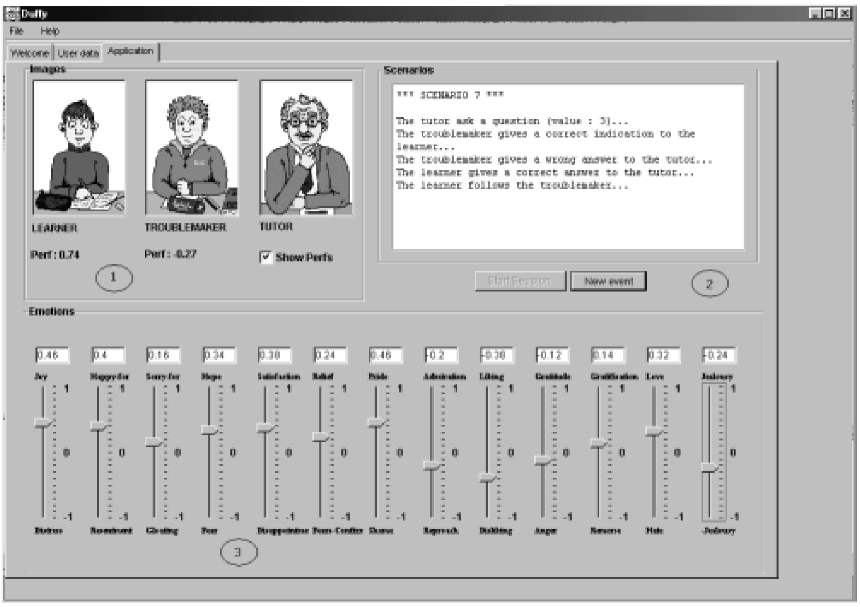

Figure 6. Affective virtual co-learner Duffy (Abou-Jaoude et al., 1999)

Duffy uses a set of emotion recognition methods and represents them with a label-based emotional matrix where emotions are matched in pairs, for example like-dislike. A student's history is kept and information on affect is also stored as a time series. A fuzzy model was used to define levels of emotional states that trigger interventions. Duffy exploits persona effect as well as a learning by disturbing strategy.

The reported outcomes of experiments with Duffy include the statement that emotional layer is more important to novice learners and less interesting for experienced ones. However, problems with emotion recognition and representation model that was not adequately defined, and problem of more sophisticated forms of affective expressions were also reported by the authors of the experiment (Abou-Jaoude et al., 1999).

4.4. Affect-aware tutoring systems – case studies analysis

The three presented case studies of tutoring systems use different methods of affect processing. As input channels for emotion recognition they use a facial expression (Eve) or user's textual inputs (Gerda). In Duffy users' events and performance with the system is being measured and anticipated emotional state is assumed. The three systems use different representation models for storing information on affect: discrete (Eve), dimensional (Gerda) and label-based (Duffy). Modalities used for affective interventions in all three cases, include textual reactions as well as avatars' animations, although the latter are obtained in three different methods: 3D avatar (Eve), actor videos (Gerda) and 2D drawing animations (Duffy). On non-technical layer, the three cases are quite similar as they all exploit persona effect to influence user emotions, although they use different interface metaphors and different roles of mentors is assumed: Eve is a coach, Gerda plays a role of authoritative teacher, while Duffy pretends to be a co-learner. Table 1 presents summary of the systems features.

Table 1. Affect-aware tutoring systems comparison

Feature	Eve	Gerda	Duffy
Emotion recognition input channels	Facial expression	Text (user input)	User events and performance history
Emotion representation model	Discrete: Ekman's six basic emotions	Dimensional: PAD scale	Label-based: matrix of label pairs
Modalities used for intervention	Textual and body language (animated avatar)	Textual mainly and elements of mimics (actor videos)	Textual and animated drawing
Interface metaphor (tutor type)	Coach	Authoritative teacher	Co-learner
Affective phenomena exploited	Persona Effect Body language	Persona Effect	Persona Effect Cognitive dissonance

Analysis of the three case studies, as well as the attempt to build an affect-aware tutoring system (Gerda), made it possible to explore complexity and diversity of affective learning tools but also to face challenges of affective learning domain.

One of the most important challenges in combining affective computing and affective learning is a sufficient and applicable emotion recognition method. As stated before, for e-education the most sufficient input channels include the ones that are available at a home computer desk, however they might be not the most reliable ones. One of the challenges is to estimate the quality of the input channel in the context of use, for example video can be available or not, if a student does not have a camera, forgets or decides not to switch it on. A video input channel is also sensitive to lighting conditions. On the other hand, the most reliable input channels, such as biomeasurements, are usually not available and can be perceived as intrusive or disturbing. A non-disturbing but reliable learner's observation is still a challenge.

Granularity of emotion recognition is one of the challenges that is nowadays intensively explored by the scientists worldwide. The best accuracy up to 98% is provided by the two-class emotion elicitation methods, which is not sufficient for learning processes. In the case of less--disturbing inputs and higher granularity levels, accuracy falls down significantly. The challenge is not only to improve the granularity (number of distinguishable emotional states), but also to distinguish the ones that are the most important from the perspective of affective learning. It can be expected that within few years accuracy and granularity of emotion recognition will improve significantly, however, they may still be not meeting the needs of affective learning processes. Another challenge is credibility of the results provided by the recognition algorithms. Even if their accuracy improves significantly (which is obviously one of the most common research objectives), there is still an issue of dealing with part-time unavailability and low quality of input channels. Research on interest classification based on selected 11 features from 4 channels using Gaussian Processes and SVM showed an accuracy of 86%, but most importantly, the significant problem of missing or noisy channels was also recognized (Kapoor & Picard, 2005). If a classifier learns using a number of features chosen from, for example, four input channels, and then one of the channels is missing, the classification accuracy may fall down significantly. One can imagine that lighting in a room may change, keyboard input can be missing (user idleness) or a sensor might be misplaced or unplugged by mistake. Each emotion recognition algorithm is fragile (in terms of accuracy) if part of the input is missing or it is noisy. Therefore, the temporary quality of the results can be estimated only by the algorithm that performs emotion elicitation process and some measure of output quality should be provided together with the result. The measures of the result quality and methods of their calculation for different emotion recognition techniques were not defined yet.

Another group of challenges is connected with affective phenomena interpretation, non-disturbing interventions and providing affect-aware control mechanisms for tutoring tools. Distinction of effective and counter-productive emotional states may depend on the educational task as well as on individual learning process characteristics. There is still not enough research done to fully explain the phenomena of affective learning and application of the findings in educational tools is another challenge.

Intensive research and implementation is performed in the domain of virtual characters representation of emotions. Avatars can perform almost any emotional state, based on face muscle movements that are under control of character visualization engine. In that area it is also possible to define two following challenges: realistic simulation of character personalities, including criteria for choosing the best virtual learning companion personality that will foster educational processes. Another challenge is an effective intervention model that would not disturb learning processes (Landowska, 2013).

5. Prospects of affective learning

Although there are so many challenges, affective mechanisms in educational environments are implementable and multiple constructive experiments were performed. In off-line technology--enhanced learning one of the most important challenges is to keep high concentration and motivation level of a learner. The most spectacular application scenarios include examples of affective learning companions and affective tutors, however, the affect-awareness mechanisms might be much simpler. Boredom and frustration which are mostly considered as ineffective in learning process, can be addressed by very simple affective interventions. Boredom can be addressed by change in task assignment, joke or other distractor (i.e. "watch out for the cat that crosses the screen") that might change fatigue into interest and attention. Frustration is usually connected with a challenge that is too hard for the learner and if so, learning paths can be adapted to fit human affect.

The affective computing method application can be also adapted in on-line training with the presence of a teacher. In virtual environments part of the face-to-face learner observation is missing (body posture, distractors) and emotion recognition might be used to support teachers to identify outliers and make better interventions.

In collaborative learning environments one of the potentials is to exploit gamification to improve learner motivation and satisfaction. Gamification is a quite popular term nowadays to describe a motivation method that uses techniques known from games. Gamification challenges are provided in order to keep balance between user boredom and frustration, which is hard to achieve if no information on user affective state is available.

The level of emotional intelligence is said to be one of the key success factors in human life. The way we deal with ourselves and with each other determines if we succeed in achieving our goals and performing our tasks. Affective issues are certainly one of the main success factors in educational processes. What would happen if we ignore them in e-learning environments? Can you imagine a system that supports a learner not only at doing math homework or taking an English test, but also helps him to remain focused and effective? Although many models and methods are known nowadays, affective learning is still a challenge for computing tools, but it is worth being explored as outcomes of educational processes influence the way people work and live.

6. Bibliography

1. Abou-Jaoude, S., Frasson, C., Charra, O. & Troncy, R. (1999). On the Application of a Believable Layer in ITS. In (AIED'99) Workshop on Synthetic Agents, Le Mans, France, July 19.
2. Ahn, H. & Picard, R. (2006). Affective cognitive learning and decision making: The role of emotions. In Proceedings of 18th European Meeting on Cybernetics and Systems Research (EMCSR).
3. Alexander, S., Sarrafzadeh, A. & Hill, S. (2006). Easy with Eve: A functional affective tutoring system. In Workshop on Motivational and Affective Issues in ITS. 8th International Conference on ITS. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.100.3683&rep=rep1&type=pdf
4. Anderson, J., Boyle, C., Corbett, A. & Lewis, M. (1990). Cognitive modeling and intelligent tutoring. Artificial Intelligence, 42(1), 7–49.
5. Ang, J., Dhillon, R., Krupski, A., Shriberg, E. & Stolcke, A. (2002). Prosody-based automatic detection of annoyance and frustration in human-computer dialog. In Proceedings 7th International Conference on Spoken Language Processing.
6. Bailenson, J. N., Pontikakis, E. D., Mauss, I. B., Gross, J. J., Jabon, M. E., Hutcherson, C. A. C., Nass, C. & John, O. (2008). Real-time classification of evoked emotions using facial feature tracking and physiological responses. International Journal of Human-Computer Studies, 66(5), 303–317. doi: 10.1016/j.ijhcs.2007.10.011
7. Baker, R. (2007). Modeling and understanding students' off-task behavior in intelligent tutoring systems. In Proceedings of the SIGCHI conference on Human factors in computing systems, ACM (pp. 1059–1068).
8. Baylor, A. (2011). The design of motivational agents and avatars. Educational Technology Research and Development, 59(2), 291–300. doi: 10.1007/s11423-011-9196-3
9. Ben Ammar, M., Neji, M., Alimi, A. M. & Gouardères, G. (2010). The affective tutoring system. Expert Systems with Applications, 37(4), 3013-3023. doi: 10.1016/j.eswa.2009.09.031
10. Bessiere, K., Newhagen, J., Robinson, J. & Shneiderman, B. (2006). A model for computer frustration: The role of instrumental and dispositional factors on incident, session, and post-session frustration and mood. Computers in Human Behavior, 22(6), 941-961. doi: 10.1016/j.chb.2004.03.015
11. Binali, H., Wu, C. & Potdar, V. (2009). A new significant area: Emotion detection in e-learning using opinion mining techniques. In Proceedings of 3rd IEEE International Conference on Digital Ecosystems and Technologies (pp. 259–264).
12. Binali, H., Wu, C., Potdar, V. (2010). Computational approaches for emotion detection in text. In 4th IEEE International Conference on Digital Ecosystems and Technologies (DEST) (pp. 172–177).
13. Boehner, K., DePaula, R., Dourish, P. & Sengers, P. (2007). How emotion is made and measured. International Journal of Human-Computer Studies, 65(4), 275–291.
14. Calvo, R. & D'Mello, S. (2010). Affect detection: An interdisciplinary review of models, methods, and their applications. IEEE Transactions on Affective Computing, 1(1), 18-37. doi: 10.1109/T-AFFC.2010.1
15. Chou, C.-Y., Chan, T.-W. & Lin, C.-J. (2003). Redefining the learning companion: the past, present, and future of educational agents. Computers & Education, 40(3), 255–269.
16. Ekman, P. & Davidson, R. (1999). The Nature of Emotion: Fundamental Questions. Oxford: Oxford University Press.
17. Elliott, C., Rickel, J. & Lester, J. (1999). Lifelike pedagogical agents and affective computing: An exploratory synthesis. In M. J. Wooldridge & M. Veloso (Eds.), Artificial Intelligence Today (pp. 195–211). Berlin: Springer Berlin Heidelberg. doi: 10.1007/3-540-48317-9_8
18. Hone, K. (2006). Empathic agents to reduce user frustration: The effects of varying agent characteristics. Interacting with Computers, 18(2), 227–245. doi: 10.1016/j.intcom.2005.05.003
19. Hudlicka, E. (2003). To feel or not to feel: The role of affect in human-computer interaction. International Journal of Human-Computer Studies, 59(1), 1–32. doi: 10.1016/S1071-5819(03)00047-8
20. Kapoor, A., Mota, S. & Picard, R. (2001). Towards a learning companion that recognizes affect. In AAAI Fall symposium.
21. Kapoor, A. & Picard, R. (2005) Multimodal affect recognition in learning environments. In Proceedings of 13th annual ACM International Conference on Multimedia (pp. 677–682).
22. Kołakowska, A. (2013). A review of emotion recognition methods based on keystroke dynamics and mouse move-

ments. In 6th Human-System Interaction Conference (pp. 548–555).

23. Kołakowska, A., Landowska, A., Szwoch, M., Szwoch, W. & Wrobel, M. R. (2013). Emotion Recognition and its Application in Software Engineering. In 6th Human-System Interaction Conference (pp. 532–539).
24. Kradinac, U. (2008). Textual emotion recognition and creative visualisation. (Dissertation). Belgrad.
25. Landowska, A. (2008). The role and construction of educational agents in distance learning environment. In Proceedings of the 1st International Conference on Information Technology Gdańsk, 19-21 May, 2008 (pp. 321–324).
26. Landowska, A. (2012a). Model afektywny dla edukacyjnego bota Gerda (Raport Techniczny Wydziału Elektroniki, Telekomunikacji i Informatyki Politechniki Gdańskiej, 27/2012).
27. Landowska, A. (2012b). Reprezentacja emocji i osobowości dla modelowania zachowania wirtualnych postaci w materiałach i środowiskach e-edukacji (Raport Techniczny Wydziału Elektroniki, Telekomunikacji i Informatyki Politechniki Gdańskiej, Polska, Gdańsk, 21/2012).
28. Landowska, A. (2012c). Wizualizator stanu emocjonalnego dla eksperymentów medycznych i badawczych (Raport Techniczny Wydziału Elektroniki, Telekomunikacji i Informatyki Politechniki Gdańskiej, 33/2012).
29. Landowska, A. (2013). Affect-awareness Framework for Intelligent Tutoring Systems (prepared for International Conference on Human Systems Interaction).
30. Li, J. & Ren, F. (2008). Emotion recognition from blog articles. In IEEE International Conference on Natural Language Processing and Knowledge Engineering, NLP-KE'08 (pp. 1–8)
31. Ling, H. S., Bali, R. & Salam, R. A. (2006). Emotion detection using keywords spotting and semantic network. In Computing & Informatics, IEEE (pp. 1–5).
32. Liu, H., Lieberman, H. & Selker, T. (2003). A model of textual affect sensing using real-world knowledge. In Proceedings of the 8th international conference on Intelligent user interfaces, ACM (pp. 125–132).
33. Mehrabian, A. (1997). Comparison of the PAD and PANAS as models for describing emotions and for differentiating anxiety from depression. Journal of psychopathology and behavioral assessment, 19(4), 331–357
34. Moreno, R. & Mayer, R. (2007). Interactive Multimodal Learning Environments. Educational Psychology Review, 19(3), 309–326. doi: 10.1007/s10648-007-9047-2
35. Neviarouskaya, A., Prendinger, H. & Ishizuka, M. (2009). Compositionality principle in recognition of fine-grained emotions from text. In Proceedings of the Proceedings of the Third International Conference on Weblogs and Social Media (ICWSM-09) (pp. 278-281).
36. Noteborn, G., Bohle Carbonell, K., Dailey-Hebert, A. & Gijselaers, W. (2012). The role of emotions and task significance in Virtual Education. The Internet and Higher Education, 15(3), 176–183. doi: 10.1016/j.iheduc.2012.03.002
37. Picard, R. (1995). Affective computing. Retrieved April 29, 2013 from http://affect.media.mit.edu
38. Picard, R. (2003). Affective computing: challenges. International Journal of Human-Computer Studies, 59(1), 55–64.
39. Picard, R. & Daily, S. (2005). Evaluating affective interactions: Alternatives to asking what users feel. In CHI Workshop on Evaluating Affective Interfaces: Innovative Approaches.
40. Picard, R. W. & Klein, J. (2002). Computers that recognise and respond to user emotion: theoretical and practical implications. Interacting with Computers, 14(2), 141–169.
41. Picard, R., Papert, S., Bender, W., Blumberg, B., Breazeal, C., Cavallo, D., Machover, T., Resnick, M., Roy, D. & Strohecker, C. (2004). Affective learning—a manifesto. BT Technology Journal, 22(4), 253–269. Retrieved from http://www.media.mit.edu/publications/bttj/Paper26Pages253-269.pdf
42. Rienties, B., Giesbers, B., Tempelaar, D. T., Lygo-Baker, S., Segers, M. & Gijselaers, W. H. (2012). The role of scaffolding and motivation in CSCL. Computers & Education, 59(3), 893–906. doi: 10.1016/j.compedu.2012.04.010
43. Rovai, A. P., Wighting, M. J., Baker, J. D. & Grooms, L. D. (2009). Development of an instrument to measure perceived cognitive, affective, and psychomotor learning in traditional and virtual classroom higher education settings. The Internet and Higher Education, 12(1), 7–13. doi: 10.1016/j.iheduc.2008.10.002
44. Sarrafzadeh, A., Alexander, S., Dadgostar, F., Fan, C. & Bigdeli, A. (2008). "How do you know that I don't understand?" A look at the future of Intelligent Tutoring Systems. Computers in Human Behavior, 24(4), 1342–1363. doi: 10.1016/j.chb.2007.07.008
45. Scheirer, J., Fernandez, R., Klein, J. & Picard, R. (2002). Frustrating the user on purpose: a step toward building an affective computer. Interacting with Computers, 14(2), 93-118. doi: 10.1016/S0953-5438(01)00059-5
46. Sheng, Z., Zhu-ying, L. & Wan-xin, D. (2010). The model of e-learning based on affective computing. In Proceedings 3rd IEEE International Conference on Advanced Computer Theory and Engineering (ICACTE), V3-269.
47. Szwoch, W. (2013). Using Physiological Signals for Emotion Recognition. In 6th Human-System Interaction Conference (pp. 556–561).
48. Tempelaar, D. T., Niculescu, A., Rienties, B., Giesbers, B. & Gijselaers, W. H. (2012). How achievement emotions impact students' decisions for online learning, and what precedes those emotions. Internet and Higher Education, 15(3), 161–169. doi: 10.1016/j.iheduc.2011.10.003
49. Van Mulken, S., André, E. & Müller, J. (1998). The persona effect: how substantial is it? In People and computers (pp. 53–66). London: Springer. doi: 10.1007/978-1-4471-3605-7_4

50. Whissell, C. (2009). Using the revised Dictionary of Affect in Language to quantify the emotional undertones of samples of natural language. Psychological Reports, 105, 1–13. doi: 10.2466/pr0.105.2.509-521

51. Woolf, B., Burleson, W., Arroyo, I., Dragon, T., Cooper, D. & Picard, R. (2009). Affect-aware tutors: recognising and responding to student affect. International Journal of Learning Technology, 4(3), 129–164.

52. Zeng, Z., Pantic, M., Roisman, G. & Huang, T. S. (2009). A survey of affect recognition methods: Audio, visual, and spontaneous expressions. Pattern Analysis and Machine Intelligence, IEEE Transactions on, 31(1), 39–58. doi: 10.1109/TPAMI.2008.52

Przetwarzanie emocjonalne i nauczanie afektywne – metody, wyzwania i kierunki rozwoju

Streszczenie

Słowa kluczowe: przetwarzanie emocjonalne, rozpoznawanie emocji, nauczanie afektywne, inteligentne systemy edukacyjne

Każdy nauczyciel wie, że zainteresowanie, aktywność i motywacja są istotnymi czynnikami warunkującymi powodzenie procesów edukacyjnych. Jednocześnie współczesne systemy wspomagające nauczanie nieomalże wyłącznie wspierają osiąganie celów kognitywnych, pomijając aspekty emocjonalne. Artykuł jest próbą podsumowania, w jaki sposób osiągnięcia przetwarzania emocjonalnego mogą być zastosowane w edukacji wspomaganej komputerowo. Zidentyfikowano cele włączenia metod afektywnych do e-edukacji i dokonano przeglądu metod realizacji tych celów. Przedyskutowano także wybrane wyzwania, prowadzone prace i przyszłe kierunki badań w zakresie afektywnego nauczania.