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Emotion Recognition and its Application in Software Engineering

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Abstract. **In this paper a novel application of multimodal emotion recognition algorithms in software engineering is described. Several application scenarios are proposed concerning program usability testing and software process improvement. Also a set of emotional states relevant in that application area is identified. The multimodal emotion recognition method that integrates video and depth channels, physiological signals and input devices usage patterns is proposed and some preliminary results on learning set creation are described.**

Keywords**: affective computing, emotion recognition, software engineering**

I. Introduction

We, humans, are often more emotional, than we wish to be, and our feelings influence the way we work, play and interact with computers. Affective computing is a domain that focuses on user emotions while interacting with computers and applications [1]. As emotional state of a person may influence concentration, task solving and decision making skills, affective computing vision is to make systems able to recognize and influence human emotions in order to enhance productivity and effectiveness of working with computers.

Emotion recognition and affective intervention are nowadays well recognized desired features of Intelligent Tutoring Systems, with primary focus on such learner affective states as flow, boredom or frustration [2]. Another areas of affective computing methods applications include: testing driver stress [3], psychological diagnosis and training [4], neuro-biofeedback [5], emotion expression with avatars [6] and more.

In this paper we primarily focus on application of affective computing methods in software engineering domain, which is a novel approach. Software engineering investigates processes of software design, development, testing and maintenance, primarily concentrating on the quality of the outputs (i.e. software). We propose application of emotion recognition in software engineering in order to design and produce systems of higher quality and usability. We select and customize emotion recognition methods and propose application scenarios in software development and testing processes.

II. Background

There are dozens of definitions of emotions [7], and in this paper we adopt the following distinction based on time: *emotion* is a reaction to stimuli that lasts for seconds or minutes, *mood* is an emotional state that lasts for hours or days and *personality* is an inclination to feel certain emotions. We use the term 'emotional state' to indicate current (temporary) state of a person irrespective of its origin (stimuli, mood or personality).

Most of the related work is dedicated to description of emotion recognition algorithms. A challenging problem of automatic recognition of human affect has become a research field involving more and more scientists specializing in different areas such as artificial intelligence, computer vision, psychology, physiology etc. A great many proposed algorithms differ mainly on information sources they use:

- visual information processing [8], [9],
- body movements analysis [10], [11],
- text input lexical analysis [12], [13],
- voice signals [10], [14],
- standard input devices [15], [16],
- physiological measurements [17].

Although many algorithms for emotion recognition are known, according to the authors' knowledge, they have not been applied in software engineering yet.

Most of the emotion recognition algorithms use discrete or dimensional models for affective state representation. The best recognized discrete model is Ekman six basic emotions, including: joy, sadness, fear, anger, disgust and surprise [18]. Each affective state is represented as a combination of the basic six – as a vector of six values ranging from 0 to1. Ekman proposed also sets of emotions

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with different cardinality (7 or 17), but the six emotions are most commonly applied as a representation model. Dimensional models represent emotional state as a point in 2D, 3D or 4D scales, differing on the interpretation of dimensions. The Whissell wheel proposes two dimensions of valence and arousal and is a basic model for emotion representation and quantification used in psychology [19]. Some other dimensional models add different dimensions to the basic ones, including an interesting PAD model proposed by Mehrabian and Russell, that adds dimension of dominance, that differentiates 'fight or escape' reactions to stimuli [20].

Another group of related work concerns products usability testing. The functional testing is often combined with emotional questionnaires that are filled in by the user after interaction with the product. This approach is used in evaluation of packages, food, cosmetics as well as in web site and commercials testing. However such approach has significant drawback: declared emotional states are the ones that a person is aware of and that have been rationalized enough to be expressed. Research shows, that there are some emotional states, that are not expressed when asked, because they are unaware, considered as unimportant or even blocked by taboos [21]. At the same time usability testing in software engineering is based mainly on eye-tracking and user experience questionnaires.

III. APPLICATION IN SOFTWARE ENGINEERING

The main purpose of our research is to use emotion recognition based on multimodal inputs to improve some components of software engineering process and to overcome the limitations of usability questionnaires. We focus on two areas of application in software engineering: usability testing and development process improvement.

A. *Extended software usability testing*

There is a lot of evidence, that human emotions influence interactions with software products. There is also a record of investigation on how products can influence human feelings [21] and those feelings make people buy or not. Therefore investigating emotions induced by products is an object of interest of designers, investors, producers and customers, as well.

Software usability depends on multiple quality factors, such as functionality, reliability, interface design, performance and so on. All of the quality indicators can be improved indefinitely, but there is a point to stop optimizing – it is a customer satisfaction. Measuring this satisfaction with questionnaires may be misleading. We propose to extend usability testing with emotion recognition based on multimodal inputs. We have defined the following test scenarios with required emotional state distinctions depending on the scenario.

Scenario 1. First Impression test

First impression is a state that is evoked mainly by visual input in human-systems interaction and is created in a very short time (approximately 5 seconds). Research shows, that in web page design first impression is a good predictor of 10-minute usability opinion [22]. Many of the websites will not have any more time to make an impression than these 5 seconds – the first impression makes the users stay or quit. In first impression testing the most important distinction is to differentiate user's *interest* (*excitement*) from *boredom* or *disgust*. This scenario is especially dedicated to web page usability testing.

Scenario 2. Task-based usability test

The second usability scenario proposed uses cognitive walkthrough method [23], which is a task-based approach. Software usability evaluation in this method usually involves identification of typical tasks (which may be extracted from use case models) and the optimal processes for performing them (possibly derived from dynamic models, user stories or user instructions). The representative user group performs the tasks in a controlled environment with camera recording, biometric sensors and keystroke analysis tools. Registered channels are then a subject to further analysis of usability and emotional state fluctuation. This scenario is dedicated rather to applications designed to help the user to perform specific tasks and not for entertainment or content access systems. The purpose of emotion recognition in task–based usability testing is to differentiate *frustration* from *empowerment*.

Scenario 3. Free interaction test

The third usability scenario proposed is based on free interaction with application, which is supposed to evaluate overall user experience. There are no pre-defined tasks to be performed by representative user group; instead they are asked to freely interact with application under examination. This scenario is dedicated for entertainment and content access systems, but other applications may also benefit. The objective of emotion recognition in this scenario is the distinction of *engagement* from *discouragement*.

Scenario 4. Comparative test

Comparative scenario is a selection or combination of methods used in previously defined scenarios performed on two software versions or on the application and the main competitive software product.

B. *Development process improvement*

In each segment of the job market the most valuable employees are those who are highly productive and deliver high-quality products or services. A similar situation is with respected software developers. Employers require high work efficiency and high quality code. Unfortunately, these two requirements are often in conflict, as a computer program developed under time pressure is usually of low quality [24], [25].

The purpose of this study is to verify the hypothesis that emotions have significant impact on software quality and developers' productivity. The aim is to answer the question on correlation between employee's emotional state and his work efficiency as well as quality of the developed software. The study will also determine the emotional states of IT professionals that support their work.

We have defined four research scenarios to explore multiple factors of the relationship between programmers' emotional states and their work, including the work environment, personal productivity and quality of developed code.

Scenario 5. IDE usability comparison

This scenario is an adoption of task-based usability test described in scenario 2. Integrated development environments (IDE) are one of the essential tools used by developers. Their advantages and disadvantages can significantly affect the emotional state of the users. Research will be conducted in a laboratory environment with biometric sensors. User group will be represented by both novice programmers - ICT students and ICT stuff with years of experience. The object of the research will be a set of popular IDEs. A developer will perform a series of programming tasks, such as compiling, debugging, refactoring, on three randomly selected environments, excluding those he uses the most frequently. Tests will evaluate the quality of those IDEs. However, the collected data will be used to investigate the individually differentiated impact of problems encountered in an IDE on developers' emotions. The goal of this scenario is to distinguish between the *frustration* and *empowerment*.

Scenario 6. Productivity and emotions

This scenario is designed to answer the question of whether and how emotional state affects the productivity of the programmer. The research will be conducted in a laboratory environment. Behavior of the maliciously prepared environment will evoke developers' emotions that may affect their productivity, measured for example by the number of lines of code per hour of work. In the first place *stress* associated with time pressure and *boredom* will be induced. The analysis of the collected data will determine the optimal emotional space for developer productivity.

Scenario 7. Code quality and emotions

This scenario, despite similarities to the previous one, should not be conducted in laboratory environment. It is hard to accurately evaluate the quality of the code developed in a short test. Therefore, to provide the reliable results, this scenario requires continuous monitoring of the emotional state of the programmer and the collection of incremental versions of the source code. Only the cross-examination of emotional states and source codes may lead to the designation of the correlation between quality and emotions. In this scenario, it is essential to detect emotions such as *empowerment*, *frustration* and *stress*.

Scenario 8. Tele and office working comparison

The last scenario is designed to detect whether there are differences in emotional states of programmers when working in office or at home. The number of telecommuters is growing rapidly in recent years. This research should be conducted in real work environments. This will be possible only after the development of reliable, non-intrusive methods of user emotional states recognition. The objective emotion recognition is to detect the whole range of emotions, particularly all those identified in the previous scenarios.

The scenarios 5 and 6 can be conducted in a laboratory environment. In this research, it is possible to use a biometric sensor to detect emotions of programmers. This will deliver more accurate recognition of emotions than with the previously developed non-intrusive methods. However, the implementation of the other two scenarios (7 and 8) will be possible only using non-intrusive methods for detecting the emotions of computer users.

As the computer is the primary working environment of programmer, the implementation of emotions recognition mechanisms in human-computer interface is a natural choice. However research, as well as proposed scenarios (except scenario 5), are sufficiently universal to be applied to many professions.

C. Investigated emotional states

According to the proposed scenarios, emotional states investigated within this research include, but are not limited to, the following ones: *excitement*, *empowerment*, *engagement*, *discouragement*, *disgust*, *frustration*, *boredom* and *surprise*. The defined set should be extended with a group of neutral emotional states, which may be considered as a reference for recognition of other emotional states. The classification must also take into account gradation of emotional states.

We have chosen PAD emotional scale for emotion representation. This model describes emotions using three dimensions: *positiveness* (valence), *arousal* and *dominance* [20]. This choice was justified by analysis of emotional states that are objects of interest in the research. Some of them were hardly expressible as a combination of Ekman six basic emotions, for example boredom. We also considered the dominance dimension as one of relevant factors to describe the states of interest.

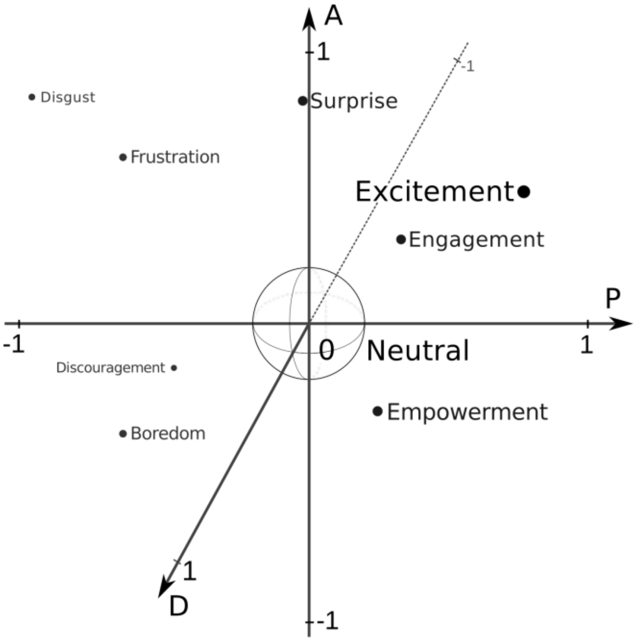

Fig. 1. Investigated emotional states represented in PAD space. The third dimension of dominance was expressed with font size for easier interpretation.

Investigated emotional states may be assigned points in PAD space, according to labels proposed by Mehrabian [20] as shown in Figure 1, however one must remember, that those labels are fuzzy concepts and representation with points is only demonstrative.

Points with coordinates close to zero may be interpreted as neutral emotional states. The states of excitement, empowerment, and attractiveness are positive, but differ on arousal and dominance. The states of frustration and boredom are negative and have low dominance value, but differ on arousal. Surprise is an active emotional state, with medium value of valence and dominance factors.

D. Emotion recognition processes

The goal of human emotion recognition is to automatically classify user's temporal emotional state basing on some input data. This can be achieved by one of many types of classifiers developed in the field of pattern recognition. As only very little classification information is known *a priori* in emotion recognition we assume the supervised learning approach for the classifier's construction.

This approach assumes several stages of classifier's construction which are: *data acquisition* and *feature extraction*, *creation of the training set* containing labeled data and *classifier's learning*. Finally, the created classifier can be used for emotion classification in different applications. All these stages are presented in Fig. 2 and described in detail in the following subsections.

E. Multimodal data acquisition

In our research we assume that emotion recognition will be based on multimodal inputs. This approach proved to provide more information to the recognition process as different data channels deliver valuable complementary information eliminating potential drawbacks of any individual input [26]. In general, information sources which are widely used in affect recognition may be divided into the following types: vision, sound, text, physiological, and standard input devices. In our research we plan to use all of them but sound. Additionally, we are going to use scene depth information from the Kinect sensor which should improve recognition of vision data.

Physiological sensors

All the physiological sensors are non-invasive but sometimes they may be intrusive or not comfortable for users. For evaluating people's emotions by physiological signals special equipment is needed. It is not possible in real-life situations when we want to determine emotions of people during usual learning or working processes. But taking specialized measurements of physiological signals can be used in some scenarios as well as for the enhancement or verification of a classifier's accuracy.

There are many kinds of physiological parameters that can be acquired using different sensors. The most popular ones are described below [27], [28].

Skin conductance (SC) sensor allows to measure changes in the electrodermal activity. During the physiological arousal skin becomes a better conductor of electricity.

Blood volume pulse (BVP) sensor measures blood pressure and heart rate, usually using the light reflected by the skin. During the measurement pressure waveform and other parameters are recorded.

Electromyography (EMG) sensor allows to measure micro electric impulses generated by muscles during their activity. The amplitude of an electric signal is proportional to the power of the muscular contraction. Muscle activity may be an indicator especially for emotions with negative valence.

Respiratory signal (RS) is a relative measure of chest or abdominal stretch. The breath characteristics change due to emotions.

Skin Temperature (T) is rather simple but useful measurement. In case of stress the blood flow in peripheral vessels changes causing for example finger temperature decrease. So, skin temperature changes reflect person's emotional states and may be used in emotion recognition.

Electrocardiography (ECG) records the electrical activity of the heart. ECG is used to measure the heart rate and regularity of heartbeats. Such activity can reflect the emotional valence.

Video and depth sensors

Using visual data, acquisition process is not intrusive for a user. We need video camera only so the equipment is very simple and easily accessible for people. The disadvantages of such approach are that image preprocessing is necessary and complex algorithms of pattern recognition are needed. For instance the difficulty of facial expression recognition is that it usually works well only in the case of a posed behavior and proper lightning. However, some results on spontaneous facial behavior have been also reported [27].

Depth sensors allow for acquiring the depth image of a scene. As the most popular depth sensors use non-visual infrared light technology they are generally resistant to common problems of RGB cameras that is to insufficient and uneven lighting conditions. That is why information from depth sensors seems to be very useful when combined with optical channel and even alone.

Since introducing Microsoft Kinect depth sensors are used for recognition of human poses, gestures and movements [30]. The first attempts to recognize human face and mimics using depth sensors are also reported [31].

Standard input devices

Standard input devices, though less popular, might be other sources of information on users' emotions [15], [16]. They enable a completely unobtrusive way of collecting data, because no special hardware is needed and moreover it may be done during users' usual computer activities. That is why we find them useful in the proposed research, both in the area of software development process and during the usability tests.

Synergy of multimodal input processing

Physiological signals are very useful for emotion recognition because people are sometimes able to control their facial expression but it is impossible or extremely difficult to control natural reactions of our body like

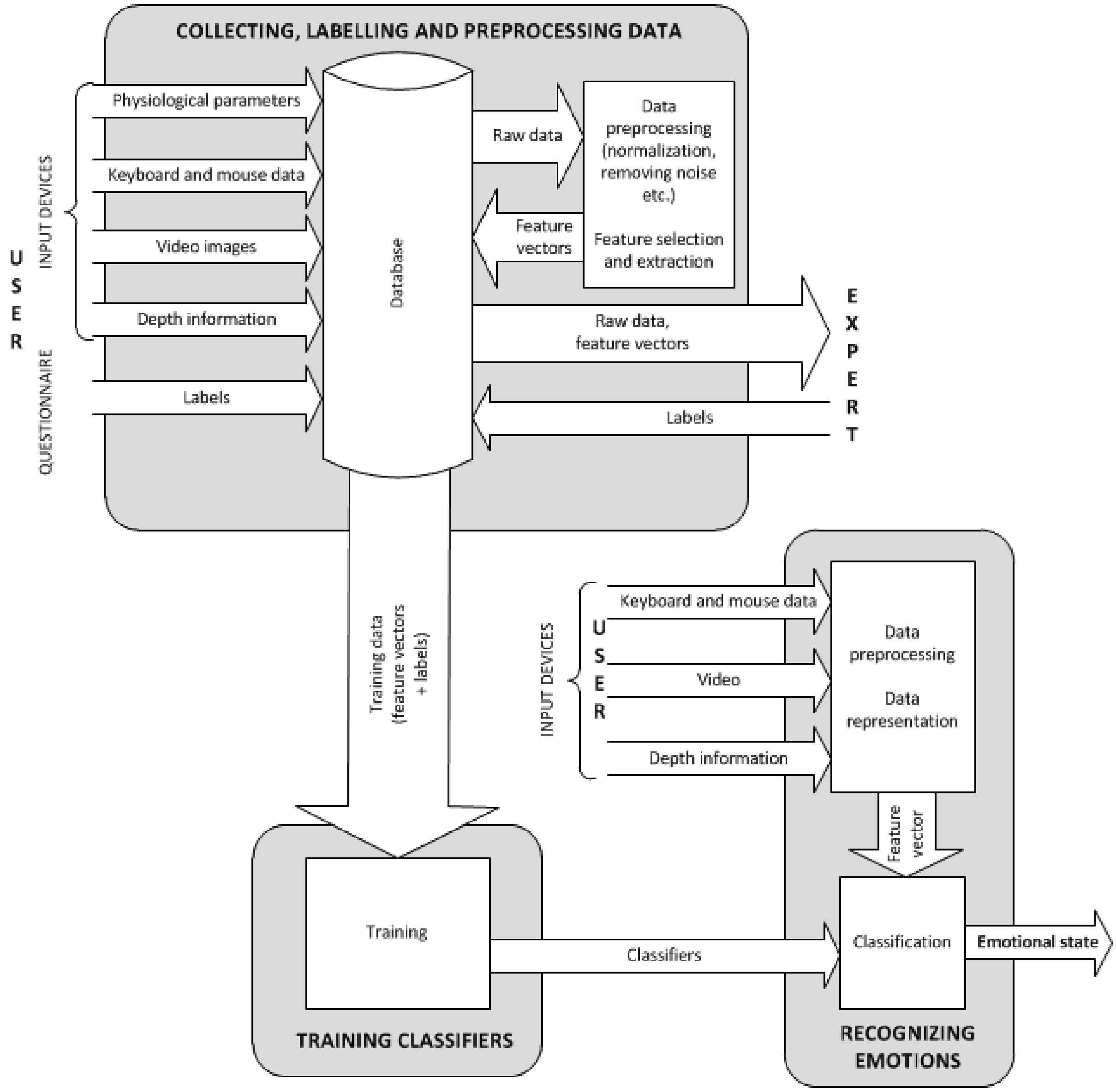

Fig. 2. The stages of an emotion recognition process

changes of temperature or heart rate [28]. In our research we plan to use physiological measurements to recognize emotional states, that will be treated as a baseline for calibration and verification of developed visual methods. Biomeasurements require special equipment which is available only in laboratory environment. Conducting tests in real environments requires methods that use equipment available at typical workstations (camera, mouse, keyboard)[32].

F. Features extraction

Multimodal input channels supply a system with a huge amount of raw data. As in real-time systems these data are sampled at certain, potentially high frequency, it is often not possible to use all of these data for emotion recognition. Fortunately, it is not needed to do so as only some features can be extracted and used for recognition process. Therefore, before starting to train a classifier, it is planned to perform a feature selection procedure to eliminate the parameters which do not correlate with the class labels and thus reduce the dimensionality.

It is possible to extract a large amount of statistical, time and frequency domain features from physiological signals. Researchers use different sets of features. J.Kim et al. [33] exploited 110 features from ECG, EMG, skin conductance and respiratory signal. Usually researchers use features like: mean, standard deviation, difference, Fourier transform, wavelet transform, high frequency and low frequency power, entropy, thresholding, peak detection etc. [28].

In our research we plan to use several physiological signals described in the previous section, as well as some higher level complex features based on these simple time series. We plan to define a small number of highly reliable features pointing certain emotion aspects such as boredom, excitement etc. These features will be used for detection of the level of user arousal and dominance.

Vision based methods are very important in the recognition of facial expression. They are based on various optical face features such as geometric or appearance ones. Geometric features describe characteristic points of the face as well as their related distances or angles [34]. These characteristic points are usually eyes, brows, nose and lips.

Appearance features are mainly based on the face colors and textures, mostly after image preprocessing [35]. Other, more complex features are extracted from transformed images such as eigenfaces. In our research we plan to use dynamic shape models as they allow for matching a model with faces in different emotional states. Additionally, scene depth information should allow for creation of more precise 3D mask models.

Many emotion recognition methods are based on the analysis of dynamic facial expressions that can be described in terms of certain sets of mimic movements. Thus we also plan to use complex temporal features such as movement vectors or tensor fields extracted for subsequent image frames from video recordings.

As it has been already mentioned, keystroke dynamics and mouse movements are also the data worth taking into account. Features extracted from keystrokes may be divided into two groups: timing and frequency parameters [36], [37]. Timing features are the duration times of single keys and key sequences (usually of length two or three) pressing, the latency times between depressing a key and pressing the next one and also typing speed. Frequency features indicate how often a user presses selected keys, such as backspace, delete, alt, shift etc. Mouse movements provide some more measurements, such as the numbers of different clicks, time between pressing and releasing a button, mouse speed and acceleration, path length, angle and direction of mouse movements [16]. A single feature vector is usually created by averaging the parameters' values taken during a predefined period of time.

G. Data labeling

There are two approaches to emotion labeling. One approach is to label emotions by a human, the second approach is automatic labeling. There are also different types of labels: labeling the emotions into discrete categories where people are able to choose from a predefined list of word labels like sadness, boredom, joy, surprise etc. and labeling using a continuous scale that allows to determine emotion gradation in terms of valence, arousal and dominance.

It is quite difficult to collect labeled data, i.e. images, signals, parameters etc. together with the information on a person's emotional state at the moment of data recording, which is necessary to perform the supervised learning. Usually the labels for the training data are assigned according to specially designed questionnaires given to the users or on the base of independent observers' evaluations. The questionnaires may incorporate common scales such as for examples the Likert scale presenting a range of responses to each question [38] or Self-Assessment-Manikin (SAM) technique, which is a graphical way of expressing valence, arousal and dominance [39].

However such labeling may not be objective, which in turn may result in poor accuracy of the trained system. To avoid this situation we are going to validate the labels provided by humans with the labels assigned on the base of physiological measurements.

H. Classifier's learning and emotion recognition

There are many different machine learning methods that can be used for classifiers creation in emotion recognition. Among them one can mark out example applications of such algorithms used in recognizing emotional states on the base of the following information:

- *facial expression:* SVM, HMM [8], decision trees[11], linear discriminant analysis [9], Bayesian networks [36], Active Appearance Models [41];
- *gestures:* decision trees[41], Bayesian networks [8], [41];
- *text:* SVM [42], naïve Bayes, decision trees, k-nearest neighbours, neural networks [43];
- *physiological signals:* SVM, Bayesian networks, neural networks, linear logistic regression, naïve Bayes [43], k-nearest neighbours [44]; decision trees [45];
- *keystroke dynamics:* decision trees [36], Bayesian networks [46], neural networks [37].

Although some methods show higher accuracies than others, it is impossible to indicate the best methodology, because the reported results are incomparable. The experiments are usually performed for different sets of data and various subsets of emotional states are recognized. However some valuable conclusions from this research should be taken into account during our study. Moreover a few other factors should influence decision on the choice of machine learning method: the types of feature values, the number of features, the number of training vectors, the type of knowledge representation, whether or not the system should be adaptive.

A model combining different sources of information will be also investigated. Such approach might be useful either if there is a problem of different feature types, which is not supported by many classifiers and appears in this research, or when the number of features after performing feature selection and extraction procedures is still high. To overcome this, the feature vector might be divided into a number of shorter subvectors and thus separated training sets are used to build separated classifiers. The final decision rule becomes a combination of all classifiers' rules. A combined rule may be also built on the base of the same training data, but using different methods. It is often possible to improve the recognition rate in this way [47].

Another essential decision which has to be made up is whether to build a single universal model on the base of data collected from all users or to create a separate personalized model for everyone. The second approach seems to be more appropriate, because it is obvious that different people may react in different ways in the case of some emotional states. One would speed up typing in case of stress while another one would pause it. However it would require more training data gathered from each user. The most interesting approach, worth investigating, would be combining both universal and individual models, depending on the type of input data and emotions recognized.

Depending on the way of training the classifiers it is possible either to build a model answering a single question *How does a user feel?*, or a number of models each answering a question about one emotional state, such as for example *Is a user stressed?*. In the first case, typical multiclass training should be performed. Every feature vector will be then assigned to one of the known classes. If there appears an unknown emotional state it will be incorrectly classified as one of the predefined emotions. In the second case one would train a number of one-class classifiers, usually used in the task of outlier detection [48]. Then a new state would not be recognized as any of the known ones, provided there is no classification error. The two approaches are going to be validated and compared during the experiments.

To sum up, an ideal emotion recognition method in the proposed real-life application would be a combination of adaptive classifiers which could cope with high number of features of different types and would be able to improve its effectiveness with increasing amounts of training data continuously recorded during users' typical activities.

IV. Preliminary results

Preliminary research on emotion recognition in human-computer interaction was conducted on a biofeedback stand. The results were rather promising, as initial sessions showed evident relations between human emotions and selected physiological signals, what confirmed the correctness of the proposed approach. The tests however revealed also the problem of sensor location. Typically temperature, skin conductance or BVP sensors are placed on fingers and are very sensitive to movements, what indicates that hands should not move. At the same time, human-computer interaction is based mainly on peripheral devices (keyboard and mouse), that require finger movements. We have identified some other sensor locations, however, that changes some signal parameters (ex. amplitudes) and the reliability of measurements must be confirmed in further research.

The video database of emotions expressed intentionally by adult volunteers was also constructed for the algorithm learning purposes. However, some of the emotions were found very hard to express by most of the participants, including excitement and anger, what indicates that they may be afterwards less recognizable than others. A training set of naturally expressed emotions should be also applied, whenever possible.

V. Conclusion

The influence of human emotions upon effectiveness of our work and the quality of the results is unquestionable. The scenarios proposed in this paper should help to evaluate the scale of this phenomenon in software engineering, which has not been investigated before. The proposed multimodal approach to emotion recognition should lead to more reliable results when compared with approaches based on a single information channel or questionnaires.

The proposed enhancements in software usability testing and its development process are expected to advance the design and implementation of systems towards better user experience.

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