User's model for user emotional state identification and user's model characteristics relevancy

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Abstract: *Researches focused on human emotions identification at work with computer reach increasing care in the area of human computer interaction and artificial intelligence. Researchers aim to recognize user´s emotions the most exactly. Condition of solution is that emotions influence work and behavior of person during the time of using computer. In this paper we are focused on user´s model biometric characteristics and its influence determination for recognition of emotions at work with computer. We propose method for influence determination of each particular characteristic inspired by calculating information gain used in classification. On the base of influence and according to properties of these characteristics we have defined own weighting coefficient, which we apply in comparative methods for emotion´s recognition. We show influence of user characteristics and how our approach increases success of emotion recognition.*

Key words: *User behaviour characteristics, identification, authentication, monitoring of user, keystroke dynamics.*

INTRODUCTION

In this paper we are focused on the user´s model for the aim of his emotions and emotional status identification. Mood, emotions, feelings and states of human are changeable in various situations, also during the time of using computer. Occur of negative emotion at work with computer is highly frequent. This fact was confirmed by symposium that we realized. Our respondents said that they have felt states as tiredness and stress periodically. But computer systems are not able to understand and adapt to user. Because of this reason computer programs react unsuitable, provide incorrect feedback, applications interrupt work and it lead to user increasing frustration. So, after successful recognition of actual user emotion in computer environment, solutions want to offer better and more effective conditions of his work.

Our general goal is recognition of emotions by modeling user according his biometric characteristics. In solution we come out from fact, that emotions influence human work and behavior during using computer. User behavior and manners affect biometric characteristics such as keystroke dynamics, mouse dynamics and work with applications. These characteristics we can monitoring and then create model from characteristics values. We understand user model as mathematical formula of person behavior that allow us to recognize user or user emotions.

Identification is realized by comparing created model with data captured from real time work with computer. In this paper we are mainly focused on selection of the most relevant user characteristics and their weighting, that lead to more exact emotion recognition.

RELATED WORK

The ability to express and recognize emotions plays the important role in human communication and once more in human computer interaction. Researches has far long time ago proved, that human has tendency to communicate and work with computer in the natural social way reflecting interactions of human at usual social events [6]. In area of human computer interaction the production of emotional intelligent system´s increases, these systems will react on human´s emotions and behavior at time of working with computer.

Solution of given assignment consist of four basic steps:

1. collect user behavior characteristics,
2. create model from collected characteristics,
3. identification of emotion by comparing models,

4. execute adequate action according recognized emotion implies recommendation or feedback.

For creating model it is necessary to collect sufficient amount of data about user and his work. For this, there are various tools, such as [2] which process data from keystroke dynamics and mouse dynamics, monitoring human´s behavior at time of using applications and development tool.

In article [1] for distinguish the emotions authors have been interested by two analyzed approaches: dimensional and categorical. In studied works of user´s emotions modeling the authors [1], [3], [4] are focused on categorical approach, where the user has the possibility to choose from concrete emotions. Dimensional approach divides emotions into groups by two dimensions: arousal and valence. Besides emotions, there is the possibility to deal with identifying states such as stress, tiredness or diseases [5].

In terms of identification, authors [1], [3], [4] promise successful results of emotions recognition by using classification and statistical methods. In article [5] mentioned advantage of using statistically pre-processed data.

For user modelling of keystroke dynamics authors using like measures digraphs, trigraphs, dwell time and flight time. For user modelling are also using mouse movement [1,13]. In biometric systems are recognized indicators of FAR and FRR. Indicator FRR is False Rejection Rate, it also uses the term False Alarm Rate, error type 1 - a legitimate user is rejected. Indicator FAR is False Acceptance Rate, also used the term Impostor Pass Rate, error type 2 - an impostor is accepted as a legitimate user.

OUR SOLUTION

We proposed method consists of user's characteristics selection and weighting. These characteristics called the metrics. We choose these metrics:

– keystroke dynamics including elapsed time between keys press and duration of a key press,

– mouse dynamic including mouse speed, mouse acceleration, scroll speed, left button clicking and right button clicking,

– work with applications including count of running applications and window status of running applications,

– computer system usage including charging of memory and processor.

Our proposed method aims to define influence of each metric on emotion recognition and this method includes two steps:

– determination of metrics relevancy,

– determination of metrics weight.

Determination of metrics relevancy

Importance of each metric is different in emotion recognition, because values of characteristics are differently impacted by emotion affecting. Determination of metrics relevancy means determination of their importance. We propose method for determination metrics relevancy inspired by calculating information gain. Information gain is usually used in classification method decision tree for setting the order of attributes in tree nodes. We propose using of this method for setting the order of metrics.

For information gain we have to know value of entropy, which describes a measure of disorder and homogeneity. Entropy is defined as (see Formula 1):

$$Entropy(S) = \sum_{i=1}^{c} -p_i * \log_2 p_i \qquad (1)$$

where S is a collection of all examples, p_i is the proportion of S belonging to class i. Classes in our solution are emotions. Then information gain is defined as (see Formula 2):

$$Gain(S, A) = Entropy(S) - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} Entropy(S_v) \quad (2)$$

where *Values(A)* is the set of all possible values of attribute A. Attributes in our solution are metrics. S_v is the subset of S for which A has value v.
On the base of information gain we find out metrics relevancy. The most relevant are keystroke dynamics metrics and order of relevancy from the most relevant is:

1. keystroke dynamics,
2. mouse acceleration,
3. mouse right button clicking, mouse left button clicking,
4. charging of memory,
5. running applications,
6. mouse speed, mouse scroll speed,
7. charging of processor.

We use metrics relevancy in following determination of metrics weight.

Determination of metrics weight

In our solution we recognize emotions by statistical methods Euclid distance and Manhattan distance, which we apply on created model of user metrics. It is advisable to use weighting in these methods. Because of that purpose we suggest own weighting coefficient. By iteration and experimental process we get final form of coefficient. Our suggested coefficient is defined as (see Formula 3):

$$weighting\ coefficient = \frac{R * x^2}{|mean - median|} \quad (3)$$

where x is multiplicity of current metric appearance, R is metric relevancy and |*mean-median*| express subtraction of mean and median of current metric values.

Influence on metrics weight has a frequency of their appearance. So value x express multiplicity of metrics appearance. More frequent metric provide more information about user’s behavior influenced by emotion affecting.

But, range of metrics values, which are highly frequent, can be huge. It can deface and make worse result. This case we can recognize from values of mean and median. Bigger range of metrics values caused bigger difference between mean and median. So metric’s multiplicity is divided by absolute value of mean and median subtraction.

At last we add metrics relevancy described in chapter 3.1 to weighting coefficient. Relevancy is express as variable R.

EXPERIMENTS

For experiments we had to get data of user behavior and emotions during work with computer. We get data form project EmLog **Error! Reference source not found.** so we have possibility to compare with their results. Provided data contains activities of 5 users. From these data we can create user’s model. In solution we create user’s model that contains 5 vectors for 5 groups of emotions. For each particular emotion group is created one vector. Vectors consist of statistically pre-processed values of metrics. We recognize 5 dimensional groups of emotions: neutral, negative excited, negative calm, positive excited, positive calm. We recognize emotions by comparing vectors with statistical method Manhattan distance.

Each recognizing emotion can be detected with certain probability. In first experiment we measure probability value of detecting correct emotion. Probability for each particular emotion is defined as (see Formula 4):

$$probability = \frac{correct\ emotion\ distance}{\sum_{e \in Emotions} distance_e} \tag{4}$$

where *correct emotion distance* is value of distance between two vectors of one, correct emotion and denominator express sum of all distances between one emotion vector and vectors of all emotions.

In this experiment we recognize emotions by Manhattan distance, which is variously weighting. We compared probability of correct emotions detecting by using various parts of our weighting coefficient. This leads to comparing several coefficients and declares our suggested coefficient as the most successful. It is visible from following graph (see *Figure **1***).

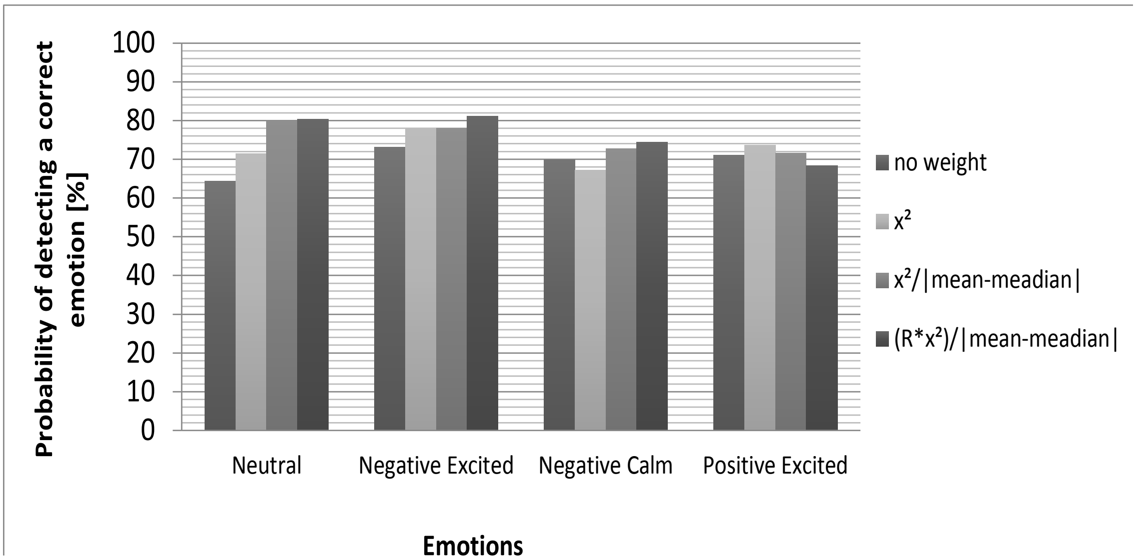

Figure 1. Increasing probability of detecting a correct emotion by using various weights

Because of that we use data from EmLog, we have opportunity to compare our results with their. EmLog evaluate solution by precision. Precision of each particular emotion is defined as (see Formula 5):

$$precision = \frac{|correct\ recognition\ of\ particular\ emotion|}{|all\ recognition\ of\ particular\ emotion|} \tag{5}$$

Comparison of precision results in our and EmLog project is visible in following graph (see *Figure 2*). Compared works use different methods for particular steps of solution and it caused differences in results.

In EmLog project they recognized 5 concrete emotions: normal, happy, stressed, tired and frustrated. So we had to toggle their emotions to our dimensional groups of emotions. It is also important to mention that EmLog project use Manhattan distance (in graph specified as VDC) and Cosine similarity (in graph specified as CSC) for emotion recognition. For now, our solution use only Manhattan distance. In our solution, model consisting of vectors contains preprocessed values of metrics from limited count of user activities. EmLog model contains all unprocessed metrics values and their count in structure like histogram.

Our solution using Manhattan distance reach better results than EmLog solution using Manhattan distance. Problem caused only neutral emotion state, where EmLog is better. It shows that problem is influenced by amount of collected activities data preprocessed into model. We plan to realize another experiment with aim to discover the most suitable amount of data.

In case of Cosine distance, EmLog reach more successful results, which ensure their model and Cosine distance method. Our success in negative emotions recognition is influenced by emotion partitioning. EmLog recognized emotions: stressed, tired and frustrated, which are negative and these states can have similar character and can be exchange to each other. Our solution recognizes groups of emotions that can be more expressly.

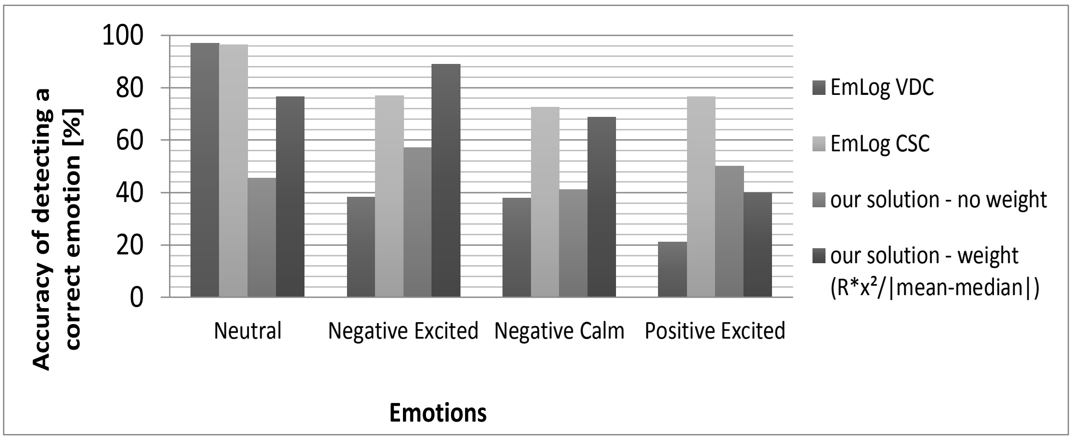

Figure 2. Comparing our solution with project EmLog

CONCLUSIONS AND FUTURE WORK

In this paper we described user´s modeling for the aim of his emotions identification. We mainly focused on users characteristics that fill user's model. We analyze properties of these characteristics that can influence emotions recognition. After that we set weighting coefficient for improving recognition. We realize experiments, where we compare our solution with another solution. Experiments results prove our contribution on successful emotion recognition.

Other possible improvement in discussed area can be reached by different model structure and various comparing methods.

In the future work we will get other users data and prove our solution on them. By applying solution on bigger dataset we will reach more precise results. Also we will apply another comparing method for emotions recognition, such as Euclid distance.

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REFERENCES

[1] Epp, C., Lippold, M., Mandryk, L.R.: Identifying Emotional States using Keystroke Dynamics. SIGCHI Conference on Human Factors in Computing Systems, (2011), pp. 715-724.

[2] PerConIK. Slovak university of technology in Bratislava, Faculty of informatics and information technologies [Online] [Cited: February 16, 2014.] perconik.fiit.stuba.sk

[3] Gajdoš, J. et al.: Odhaľovanie emocionálneho stavu používateľa. Team project, Slovak university of technology in Bratislava, (2013).

[4] Lv, H.R. et al.: Emotion recognition based on pressure sensor keyboards. IEEE International Conference on Multimedia and Expo, (2008), pp. 1089-1092.

[5] Vizer, L. M., Zhou, L., Sears, A.: Automated stress detection using keystroke an linguistic features. International Journal of Human-Computer Studies, (2009), vol. 67, no. 10, pp. 870- 886.

[6] ZIMMERMANN, P., et al.: Affective computing – a rationale for measuring mood with mouse and keyboard. International Journal of Occupational Safety and Ergonomics, (2003).

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The paper has been reviewed.