WORKSHOP

Emotion and Computing

Current Research and Future Impact

Introduction

Due to the increasing digitization, more and more adequate interfaces between the human and the digital world are needed. This includes the human emotion as one aspect of communication. The workshop series focuses on the role of affect and emotion in computer systems including the three research areas of emotion recognition, emotion generation (or expression) and emotion modeling, with special attention to AI specific problems and applications. Both shallow and deep models of emotion are in the focus of interest. Because emotional statements are often not formulated in terms of logic, it would be interesting to see how uncertain and vague notions and unconventional logic models could be used. Emotional or affective computing has drawn a strong interest in various fields from speech synthesis and dialogue systems to virtual reality and robotics. One popular application context for the various affective computing techniques is gamification, serious games and educational software systems. An extension of the conventional notion of affective computing is to add character and personality traits into the equation. The goal of the workshop is to provide a forum for the presentation of the research done towards emotions and computing as well as the existing and possible future applications of this domain. The aim is to spark a lively discussion among academics, researchers and the industry.

Contact

Further information on the workshop series can be found on the following website:

www.emotion-and-computing.de

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"Initial Investigation of Combining Electrodermal Activity Recognition with Thermal Imaging for Emotion Classification"

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Demo and Discussion Session: Affective Computing in VR and AR

demonstrations of affective computing examples in virtual and augmented reality

Initial Investigation of Combining Electrodermal Activity Recognition with Thermal Imaging for Emotion Classification

Simone Schneider[1], Dirk Reichardt[2]

[1] IBM, simone.schneider@de.ibm.com
[2] DHBW Stuttgart, dirk.reichardt@dhbw-stuttgart.de

Abstract. In recent publications, thermal imaging has been explored in order to determine brain activity. Furthermore, electrodermal activity is linked to emotional reactions of a human. In our project we combined both approaches in an experiment to find out about potential effects and benefits from a sensor fusion. First results show reasonable classification potential using a selection of pictures from the GAPED database to induce emotional reactions.

1 Introduction

The recognition of human emotions from physiological reactions of the body is not a new field of research [1 ,2 ,3, 4], nevertheless, the rising interest in wearable technology and the availability of bio sensors draw attention to this way of emotion classification. In addition, the thermal activity analysis of head and face have recently led to classification of emotional arousal [5] and the use of thermal imaging to classify emotion for improved human-robot interaction [6] is also a topic of research. In this context classifying physiological reactions to emotions would be a great achievement in order to see what a human communicates without saying anything. The term of emotion is being discussed in the research areas of psychology, neuroscience and philosophy. Yet it is not possible to create a universally valid definition of the term, only different theories like the ones from Darwin [7], Plutchik [8] and Ekman [9] can be considered. Some theories like Ekman’s describe basic emotions. Apart from that the scientist has an approach for classifying facial expressions to emotions with the FACS [10]. Therefore, the basic emotions of this theory are used to examine our hypotheses for this paper if it is possible to classify the combination of physiological reactions with the examples electrodermal activity and thermal imaging to emotions. Moreover, we want to find out if the combination of both reactions allows us to make a better classification than considering them separately.

1.1 EDA – electrodermal activity and emotions

Electrodermal activity (EDA) measurements are based on the skin conductance, which is determined by sweating. Skin conductance is an indication of emotional arousal because of its straight connection to the autonomic nervous system (ANS). The ANS is the actuator for reactions concerning external stimulations of the environment, which includes changes of the emotional mood [11]. Among others, the eccrine sweat glands are activated through the release of neurotransmitters like acetylcholine which enable a fast forwarding of stimuli. Because of having a high conductivity, the wetting of the skin through the sweat glands increases the skin conductance immediately. This can be measured as EDA through electrodes typically affixed on the palm of the hand and declared in Siemens (S)[12]. Independent from the biological background of the ANS comparative psychophysiological studies [1] also name an increase/decrease of EDA activated due to different emotions. Previous work has shown the relevance and application scenarios of EDA especially to determine stress levels [13,14].

1.2 Thermal imaging and emotions

Thermal imaging is able to illustrate immediate changes of the body heat as easily can be perceived when a person gets a red heat in uncomfortable situations. A fast change of the body temperature is typical for emotional reactions. Physiologically this relates to the sympathetic nervous system belonging to the ANS, which takes effect on unconscious reactions. In situations where a person is afraid, the hormone noradrenaline is released in preparation for an elopement associated with physical effort. With this the vessels contract and the skin is less supplied with blood which results in a cooling of the skin. This process can be reversed for other emotional reactions where the body temperature increases. Thermal imaging is fairly easy to detect with a thermal imaging camera. Further studies also indicate that facial thermal variations can be used to determine the emotional state of a person [4, 5, 6].

1.3 Hypotheses and aim of our study

Our work has explorative character at the current stage. Assessing thermal imaging and skin conductance together in a controlled experiment should give insight in potential combinations of both indicators as well as correlations. Because of their independently attested relation to emotions, it is possible that the new approach of the combination of physiological features obtains a range of values, which can be classified to a certain emotion. Along with this, the current emotional mood of a person could be measured.

2 Experimental setup

The assessment of physiological data needs an experimental setup, which first induces an emotion and then takes the measurements of the participants electrodermal activity and thermal variations, which are shown as a consequence of the emotion. The idea of the setup is to provoke emotions at subjects with the help of previously categorized pictures and measure the EDA and thermal imaging during this process.

2.1 Picture Selection

The pictures are chosen from the Open Source Geneva Affective Picture Database (GAPED) which serves irritant pictures from both positive and negative categories. In a previous study, it was academically proven which affection evaluated in arousal and valence these pictures have on subjects [15]. Table 1 illustrates the chosen pictures for our experiment already sorted to the order in which they are shown during the experiment. Altogether eleven pictures were chosen but only the last ten pictures are relevant for the later analysis. Apart from that, we need a concrete basic emotion for each picture so that the EDA and thermal imaging can be matched not only to the arousal and valence given positive/negative classification later. For this, there has been an interview with 30 subjects where the task was to assign every picture to one basic emotion of Ekman, which are disgust, rage, joy, surprise, sadness and contempt [9]. The theory of Ekman is chosen because of the previously discussed problem of different emotion theories and the need of classifiable basic emotions, which are severed by this theory. In each case, the mostly named basic emotion is assigned to the picture (table 1).

Table 1. GAPED Picture selection for experimental setup with dedicated categories

Short Description	Database Token	Positive/Negative	Basic Emotion
Bicycle	N017/Neutral	Neutral	Out of Scope
Sleeping Baby	P007/Positive	Postive	Joy
Starving Children	H077/Human Rights	Negative	Sadness
Spider	Sp136/Spider	Negative	Disgust
Ice Landscape	P130/Positive	Positive	Joy
Animal Test Ape	A041/Animal Mistr.	Negative	Contempt
Seascape	P067/Positive	Positive	Joy
Dead Person	H022/Human Rights	Negative	Sadness
Cow at Butcher	A075/Animal Mistr.	Negative	Contempt
Puppies	P114/Positive	Positive	Joy
Smiling Baby	P041/Positive	Positive	Joy

2.2 Realization

Overall, 25 subjects, 15 male and 10 female, participated in the experiment. The average age is 34 years with the youngest subject being 13 years and the oldest one being 74 years old. Before starting the experiment, everyone is asked if we are allowed to show harsh pictures. Because of five females and one male refusing this their picture order excludes the ape animal test and the cow at the butcher. To ensure comparability between the different subjects the experimental set up and with this the picture order for everyone is the same. The EDA sensor is placed on the left-hand palm of every participant and the thermal imaging camera is placed about 30 cm in front of the persons face to measure the temperature of the left cheek. Every picture is shown ten seconds, which is enough time because of EDA and temperature being closely related to the ANS. During the whole experiment, both values are continuously measured. After this, the subject is asked for feedback so that special characteristics of each person can be retained. In postprocessing for evaluation of the experiment for each picture an average value of EDA and temperature of each person is calculated.

3 Results

3.1 General Results

The first general result is that EDA and thermal imaging can be used to prove emotions. This encourages the results of already realized studies. More over our experimental setup features that every subject reacts individually to the shown pictures. Even though the previous interview could match a basic emotion with distinct majority to every picture these are not always represented in the EDA and thermal imaging. The test persons react differently in intensity and tendency to the different emotions. Because of this, for each picture the average value of both is calculated and within the categories positive/negative and the basic emotions the value ranges are declared. With the average value of all subjects it is possible to find a tendency for every basic emotion. Therefore table 2 illustrates the fundamental results which accomplishes our hypotheses of classifying emotions to the physiological reactions. Even though it is also possible to allocate EDA and thermal imaging separately to the basic emotions considering them from another is not as precise as considering both value ranges together. Only with the combination of physiological reactions it is possible to prove our hypotheses.

Table 2. Assignment EDA and thermal imaging to basic emotions

Basic Emotion	EDA	Temperature
Positive/Joy	Decreasing (-0,028 - -0,05 µS)	Rising (0,021 – 0,184°C)
Negative	Rising (0,009 - 0,052 µS)	Rising (0,024 – 0,34°C)
Sadness	Rising (0,046 - 0,052 µS)	Rising (0,164 - 0,34°C)
Disgust	Weakly Rising (0,006 µS)	Weakly Rising (0,02°C)
Contempt	No clear tendency (-0,022 - 0,007 µS)	Decreasing (-0,058 - -0,274°C)

Another result is that the emotion sadness is the most obvious and intensive to identify. In contrast to this the emotion disgust is the less obvious and intensive emotion. Because the emotion contempt belongs to the animal mistreatment pictures and this basic emotion has already been controversial in the interview with the lowest majority, the uncertainty concerning the basic emotion can also be recognized at the assignment with a not clear tendency for EDA.

3.2 Gender and Age Influence

Splitting up the test group into male and female reveals that the different sexes distinguish in their reaction to the pictures. They differentiate in intensity and the general awareness of emotion. Against the prejudices of society, women are not more emotional than the men they just differentiate in which actuator they react more to.
Another grouping of the subjects by age (13-35 years and 36-74 years) shows that there is a strong difference between how younger and older people react to the pictures. Conspicuous at the group with the older test persons is that they react either very intensive or nearly not at all.

3.3 Other Results

An interesting side effect of the experiment is that the EDA and thermal imaging represent how the personality of a person in general is. It is very easy to ascertain only by reference to the measurements if the person is emotional or calm. Apart from that, memories concerning the pictures can influence the intensity of the EDA and thermal imaging change. The feedback of the test persons on very intense reactions to some of the pictures often belongs to a personal experience they had in the past.

5 Conclusions and future Work

The results of our study have to be representatively proven with more test persons both in the interview and in the measurements of EDA and thermal imaging. With this, other vital parameters like pulse and breathing for an even more precise classification could also be measured. In a greater test series, the number of pictures could also be increased with more pictures for every basic emotion to specify the tendency for each emotion more accurate. Ekman’s theory also offers another benefit because of the already existing research in the field of face recognition with FACS [10]. The physiological measurements could also be combined with the facial expression of a person for improving the certainty of both approaches. Apart from that, it could also be helpful to use Plutchik’s theory approach of combining the basic emotions to more accurate ones [8]. With this, the problem of uncertainty for a picture could be solved.
Moreover, the different groups of test persons could be further analyzed. The differences between the emotions of men and women could be considered as well as the impact of social media and media in general to our awareness of pictures. The feedback of the older group to the question why they often reacted extremely intense was that they do not watch harsh movies and do not us social media as distinctive as the younger generation so they are not used to this kind of pictures.

In conclusion, our hypotheses if it is possible to classify emotions only by reference to EDA and thermal imaging, applies. It is possible to allocate ranges and tendencies for basic emotions to see what a human communicates without saying anything. This could be used to help people who are not able to tell what they feel. With the approach of machine learning we could even be able to predict how a person will be feeling in a certain situation which could be helpful for example in a catastrophe situation. Nevertheless, as long as there is no comprehensive definition for the term emotion as long even the most accurate physiological measurements can just concern to one emotion theory. It should also always be on our minds that the emotions of a human being are very sensitive and every person has an individual personality for which the generalization it carefully to be considered.

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Feel Your Machine: Investigating the Usage of Operation Data to Increase Awareness of Electronic Devices States Via Simulated Emotions

Alia ElBolock[1], Ahmed Youness[1], Yomna Abdelrahman[2], and Slim Abdennadher[1]

[1] German University in Cairo, New Cairo 11432, Egypt
[2] University of Stuttgart, 70569 Stuttgart, Germany
{alia.elbolock,ahmed.youness, slim.abdennadher}@guc.edu.eg
[3] {yomna.abdelrahman@vis.uni-stuttgart.de

Abstract. One of the main causes of a reduced life time of our daily electronic devices is the lack of the user awareness of it's state and usage pattern. Recently, the raise of affective computing allowed computers and machines to monitor, identify and adapt according to user's states and emotions. However, there is another under explored preservative, namely how users would monitor and adapt to the state of their machines. Where there is the typical battery state and connectivity indicators, on the other hand in this work we introduce *Emotional Companion* to investigate how computers could be given human-like emotions by mapping the computer usage parameters to human emotions. Additionally, we conducted user study with 15 participants to explore how users would react to the artificial emotions generated by the machine. We evaluated 4 emotions using emojis as the primary means of emotion representation, based on the battery and CPU usage. Our findings imply that user's awareness of their devices state increase when using human-like emotions.

Keywords: First keyword · Second keyword · Another keyword.

1 Introduction

Affective computing is a growing field with interesting and life-improving results emerging every day. Its resulting finding vary from product buying suggestions based on facial sentiment analysis [1] to aiding users in the least obtrusive ways [24, 8, 7]. With the raise of affective and state awareness research, it extended to include both humans and machines.

The main concern of Affective Computing is the user and his/her state. However, with the increasing number of daily electronic devices embedded ubiquitously in our environment, another aspect of affective computing arises. Introducing a focus on both affect and emotions from two different perspectives; (1) how computers and all applications can adapt to human affect and (2) how these artificially intelligent agents can be given artificial emotions. The work done in this paper focuses on affective computing from the second perspective.

Mobile phones and computers are now used on regular daily basis and are indispensable companions. An infographic [4] shows that the average users change their mobile phone every 1.8 years and their laptops/desktops every 3 to 5 years. The prices of all these devices are rising and the need for them is increasing. If every user were to follow the precautions needed for dealing with these devices their lifetime would increase dramatically. However, this is usually not the concern of humans as they want to get their daily endeavors done.

On the other hand, the Computers As Social Actors (CASA) theory [12] states that people unconsciously deal with computers and other media devices as if they were real humans. The work presented in this paper bases on this theory for the benefit of our daily artificial devices and in return the benefit of humans. Hence, in this work we aim to explore two main aspects; (1) how to simulate human-like emotions for our daily devices and (2) how using this representation influence the user's awareness and adaptiveness to their devices state. Would a user not want to know if its device is about to stop responding due to its CPU being over-worked? Would this not cause humans to pay more attention to the needs of their artificial companions?

In this work, we advance the state-of-the-art of artificial emotions through the following contributions:

- We propose a method for representing the state of the device using human-like emotions by using emojis based on two metric; battery and CPU usage.
- We evaluated the influence of using our approach on the user's awareness through a user study. It shows that users were more *affective-aware* of their machines when presented with emojis as opposed to the typical device indicators, such as low battery alerts.

This paper is organized as follows. First we start by giving a brief review of the state of the art followed by detailing the architecture of the emotional devices. Next, the study design is explained in detail. After that the results of the experiment are shown followed by a discussion thereof. Finally, the paper is concluded with the main findings from our evaluation.

2 Related Work

Affective computing studies what triggers the users frustration and anxiety and tries to eliminate that. For instance, [16] demonstrated that in many cases the computer user's feel frustrated while dealing with it. However, after designing a system that detects user frustration and adapt accordingly, the users reported that the frustration was reduced.

Researchers explored the usage of affective computing to enhance user experience [21, 15]. [17] presents a new approach where computer wearables can be

[4] https://www.webpagefx.com/blog/wp-content/uploads/2016/08/how-many-devices-will-you-use-in-your-life.png

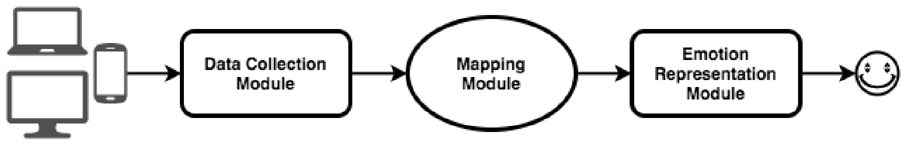

Fig. 1. Architecture of the Artificial Emotions Simulator

used side by side with the questionnaires to know who does a human feel or to know if he/she is saying there honest opinions.

There are different techniques to represent emotions, ranging from simulation of human-like emotions to abstracted representations of emotions. The Kobian humanoid robot presented in [24] exhibits facial and body expressions.[3] claims that machines that can express emotions can have a great impact on users and can affect their decisions.

In [14] and [22] colors were used as an abstracted representation of emotions. The basic human emotions were mapped to colors enabling the expression of human-like emotions suing simple means. The issue in this approach is the fact that although some colors are commonly associated with specific emotions, most of them are not. There are huge cultural and background factors that come in play when dealing with meanings of colors.

Popular emotion representation tool is emojis. In [9, 10] they reported that emojis is a deeper way of communication between people and can have different interpretations based on the sender and receiver. More than 92 % of the internet users use emojis to express themselves. In addition, emojis are sometimes easier than the commonly used languages as it is in some way multilingual. This is why emojis were finally chosen as the means of emotion representation of the presented system.

There are many different factors that affect the computer or mobile device. For instance [23] showed that constant WIFI usage can have a great impact on battery life. For instance, if the downloads are scheduled the battery would not be consumed in a short time and the CPU usage would not increase. Furthermore, [19, 11] declares the CPU usage, battery and memory usage as the most important measures of efficiency of applications, mobiles and computers.

Emotions can have a great role in decision making. There are different representations of emotions and their basic set. [18] includes eight basic emotions: anger, disgust, fear, joy, sadness, surprise, acceptance and anticipation. [4] presents six basic emotions consisting of a subset of the ones presented in [18]; namely all without acceptance and anticipation. Finally, [6] presents a recent study based on advanced technology to study emotions. The work tried to further narrow down the emotions defined in [4] to the most basic emotions. Facial recognition tools were used to try and extract the most basic ones. This further narrowed down the set to only four basic emotions: joy, sadness, surprise/fear and disgust/anger by combining surprise with fear and anger with disgust.

For the purposes of our work the narrowed down set of the four emotions was used to not overwhelm the user. Another concern in the study of emotions is the their trigger. In [13] it is stated that the human brain's activity increases as it senses or generates emotions.

In[18] states that neuro-biological theory proves that the decision making process is mainly driven by emotions. Of particular interest is [2] which found that computers triggered empathetic emotions in humans just like other humans would.

To the best of our knowledge, no tools mapping computer and phone usage data to artificial emotions exist. However, there are various tool that collect and present the usage parameters to the user in a direct way [19, 11, 5].

3 Emotional Companion

Emotional Companion is an artificial emotions simulator. Its architecture is designed in a simple manner. This is to ensure efficiency while using it without depleting the important device resources. This was the main concern in the design. Also, to ensure its portability, the system was implemented on different platforms as proof of concept. All three existing versions, Linux, Windows and Android-based, have almost the same architecture.

The simulator consists of two main components as well as a processing component, as illustrated in Figure 2. The usage data collection module records battery status, temperature as well as CPU and memory usage. This data can be seen represented in plain alpha-numerics whenever the task-manager view of the application is opened. The mapping module consists of equations that translate the usage data to emotions. The equations were chosen based on user questionnaires to choose the most mappings most intuitive to the users. The parameters illustrating the final used mappings can be found in Table 1.

Emotion	Battery	Temp.	CPU	Usage Intervals
Happy	High	Low	< 50	$<$ 5min
Neutral	Moderate	Low	< 50	$<$ 5min
Surprise	-	-	> 50	$<$ 2sec
Angry	Low	High	> 85	-

Table 1. Parameters of Mapping Emotions to Operation Data

The usage interval represents the interval between keyboard strokes and mouse clicks and movement. The device experiences surprise if the CPU usage rises to greater than 50% in a short time interval or if the usage interval decreases to less than 2 seconds. anger if any of the three shown parameters (battery, temperature or CPU) reach the value shown in Table 1.

The emotions representation module takes the emotions resulting from the mapping module and displays them as the device's own using **emoji**-based emotions. Where the emoji-based representation associates the different chosen emotions to their existing emoji counterparts. The emojis appear as a small circle in the any screen corner chosen by the user. The main concern in all the choices was to make it as non-intrusive and as integrated as possible. Also, any glaring pop-ups or constant nagging to the user was avoided to prevent from distracting the user. The main inspiration for this was to learn from Microsoft Office's Clippy; the now deprecated office assistant of many Microsoft Office applications from 1997 till 2004. According to [20], annoying and distracting characters are one of that main causes that make people detest or stop using similar agents.

4 Study

To investigate the influence of the generated emotions by *Emotional Companion* on user's usage, awareness and adaptiveness to their devices' state. In other words, would users actually respond to the needs of their devices if they report human-like emotion, we conducted a user study with the aim to investigate the behavioral change of humans towards their devices when they show their needs as emotions instead of as numbers.

4.1 Design and Apparatus

We applied a repeated-measures design, where all participants were exposed to all conditions. We studied the effect of *Emotional Companion* on the the response rate of the users to their devices in case they requiring charging or a break. For the baseline, we collected the data when the participants where using their devices regularly.

In our study, we deployed *Emotional Companion* on the participants.

4.2 Participants and Procedure

We recruited 15 participants (1 female) with age range 18 to 44 ($Mean = 23.2, SD = 2.35$) using university mailing lists. Participants were students of different majors ranging from computer science to management and university staff.

In our study we compared the the battery and CPU usage values with and without the addition of simulated emotion to the computer. The aim was to see if by changing the way the computer shows its status, the status itself would be attended to quickly and thus improved on the long run.

None of the participants had any previous experience with *Emotional Companion*. After arriving in the lab, participants filled in their demographics and signed a consent form and received an explanation of the purpose of the study.

Baseline Data Collection First, we installed an application to collect the regular usage data. The application starts automatically in the background as long as the devices are running. The application automatically tracks the needed statistics about the device usage; namely battery and CPU usage. Only these two factors were considered during the experiment to limit the number of variables in the experiment and thus have a more severe and well-defined test. No intervention is required from the user at this phase. The aim of the pretest is to give insight on the regular usage patterns of the user and the general state of the device. It is measured if the device often crashes or operates on constant high CPU percentage. It also measures if the battery is being stained by always being depleted before recharging. These statistics are automatically sent from the devices to be stored by consent from the participants. This task spans over two weeks.

***Emotional Companion* Data Collection** Next, after two weeks, we re-invited participants collect the baseline data and to install *Emotional Companion* on their devices. They are given a second application which is similar to the first one with only one addition: emotional display.

The participants are asked to use their computers as they always would and check if the emotions expressed by their devices triggers them to do any actions. They should only perform an action if they feel they want to. The application now displays a small emoji in the screen corner preferred by the user representing its current mood i.e. internal state. The same metrics as in the pretest are collected from the computer and automatically stored. The participants use their devices with the emotion simulator for another two weeks.

Post Task Questionnaire After finalizing both phases of data collection, the participants are presented with a questionnaire to investigate their general feelings towards the application and experiment they undertook. The questionnaire consisted of fourteen questions ranging from basic personal information to whether or not the application was likable. This was done because subjective evaluation relating to the user experience should be considered alongside the objective evaluation. The aim of any tool is aiding the user and providing an enjoyable experience. This gives important insight into whether we are on the right track and what could potentially be changed.

5 Results

The data collected from the study is compared using statistical analysis. We used Null hypothesis significance testing (NHTS) to test whether introducing the simulated computer emotions via *Emotional Companion*, produces no change in the usage behavior and awareness as well as Cohen's d, as shown in Table 2.

Moreover, the feedback from the questionnaire of the participants was analyzed. The questionnaire consisted of 14 questions asking the participants how

	p	d
CPU	0.14	0.42
Battery	< 0.001	0.35

Table 2. Results of the NHTS and Cohen's d for the CPU and Battery usage

they felt about the experiment and the device emotions simulator they tried. Table 3 illustrates the results of the questionnaire.

Question	Result
Rating of application without emotions	3.5/5
Rating of application with emotions	4.5/5
Continuation of using the application	4.3/5
Recommend-ability of application	4.6/5
Acceptance of conflicting emotions (device/user)	4.3/5
Change of user's feeling towards device	4.27/5
Happiness rating while using 2nd application	4.6/5
Suitability of emojis for representation	4.6/5

Table 3. Post Task Questionnaire Results

6 Discussion

The experiment produced two different results, that will be each separately discussed. The experiment was divided into two parts: the pre- and post-test to ensure its internal validity. Then, each of the two variables being tested was analyzed independently to get clean unambiguous results.

In case of the battery usage, the t-test proved that having the device convey its needs as emotions showed significant changes in the user's behavior. This is probably the case as plugging in the battery is usually ingredient till the last minute due to concentration in the task at hand or simply laziness. In case the users are doing something important, they probably will not stop it even if the computer showed its emotions. In the second case of laziness, the user could be triggered to respond to the needs of the device if it relates more to it. So, in the case of the battery the strong statistical result produced can be seen as evidence that the wider aim of the experiment was fulfilled. This is because it initially showed significant behavioral change in the participants when introducing the simulated emotions.

In case of the CPU usage, the t-test showed that the results of the experiment were insignificant. There are many reasons for this that will be discussed below:

1. The CPU usage does not variate as often as the battery does. The battery usage follows a repeating pattern of depletion and recharge. In contrast, the

CPU is usually operating at a steady rate and only spikes on occasion making it harder to detect through the statistical analysis.
2. The state and age of the devices used in the experiment severely affect the results of the CPU usage, as they prevent the CPU from being overworked.
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7 Future Work and Conclusion

In the future it would be interesting to deploy the same study on a larger sample while addressing the issues discussed above. An accompanying program could be given to the participants that ensures the occurrence of the required events while monitoring the user's responses. This would result in a more constrained experiment environment; providing more apparent results but harder to generalize. Different statistical analysis techniques could be used in the future to give different insights. The experiment could also run for a longer period to be able to better test the behavioral change in such a low impact experiment. The pool of participants can also be manipulated to test against different occupations, backgrounds and genders. Finally, it would be interesting to investigate the effect of various possible emotion representation methods, as the response of the participants could easily be affected by that. The discussed variables should each be manipulated one at a time to avoid resulting confounds.

The paper presented a tool for simulating the emotions of devices based on their internal physical statistics. The aim was to investigate whether humans would relate more to their computers if they conveyed their states as emotions represented through emojis. We conducted an experiment that compared explicit emotional representation through emojis with no emotional representation through statistical number. The results showed significant behavioral change in case of the battery usage but not in that of the CPU usage.

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Feel Your Machine: Investigating the Usage of Operation Data to Increase Awareness of Electronic Devices States Via Simulated Emotions

Alia ElBolock[1], Ahmed Youness[1], Yomna Abdelrahman[2], and Slim Abdennadher[1]

[1] German University in Cairo, New Cairo 11432, Egypt
[2] University of Stuttgart, 70569 Stuttgart, Germany
{alia.elbolock,ahmed.youness, slim.abdennadher}@guc.edu.eg
[3] {yomna.abdelrahman@vis.uni-stuttgart.de

Abstract. One of the main causes of a reduced life time of our daily electronic devices is the lack of the user awareness of it's state and usage pattern. Recently, the raise of affective computing allowed computers and machines to monitor, identify and adapt according to user's states and emotions. However, there is another under explored preservative, namely how users would monitor and adapt to the state of their machines. Where there is the typical battery state and connectivity indicators, on the other hand in this work we introduce *Emotional Companion* to investigate how computers could be given human-like emotions by mapping the computer usage parameters to human emotions. Additionally, we conducted user study with 15 participants to explore how users would react to the artificial emotions generated by the machine. We evaluated 4 emotions using emojis as the primary means of emotion representation, based on the battery and CPU usage. Our findings imply that user's awareness of their devices state increase when using human-like emotions.

Keywords: First keyword · Second keyword · Another keyword.

1 Introduction

Affective computing is a growing field with interesting and life-improving results emerging every day. Its resulting finding vary from product buying suggestions based on facial sentiment analysis [1] to aiding users in the least obtrusive ways [24, 8, 7]. With the raise of affective and state awareness research, it extended to include both humans and machines.

The main concern of Affective Computing is the user and his/her state. However, with the increasing number of daily electronic devices embedded ubiquitously in our environment, another aspect of affective computing arises. Introducing a focus on both affect and emotions from two different perspectives; (1) how computers and all applications can adapt to human affect and (2) how these artificially intelligent agents can be given artificial emotions. The work done in this paper focuses on affective computing from the second perspective.

Mobile phones and computers are now used on regular daily basis and are indispensable companions. An infographic [4] shows that the average users change their mobile phone every 1.8 years and their laptops/desktops every 3 to 5 years. The prices of all these devices are rising and the need for them is increasing. If every user were to follow the precautions needed for dealing with these devices their lifetime would increase dramatically. However, this is usually not the concern of humans as they want to get their daily endeavors done.

On the other hand, the Computers As Social Actors (CASA) theory [12] states that people unconsciously deal with computers and other media devices as if they were real humans. The work presented in this paper bases on this theory for the benefit of our daily artificial devices and in return the benefit of humans. Hence, in this work we aim to explore two main aspects; (1) how to simulate human-like emotions for our daily devices and (2) how using this representation influence the user's awareness and adaptiveness to their devices state. Would a user not want to know if its device is about to stop responding due to its CPU being over-worked? Would this not cause humans to pay more attention to the needs of their artificial companions?

In this work, we advance the state-of-the-art of artificial emotions through the following contributions:

- We propose a method for representing the state of the device using human-like emotions by using emojis based on two metric; battery and CPU usage.
- We evaluated the influence of using our approach on the user's awareness through a user study. It shows that users were more *affective-aware* of their machines when presented with emojis as opposed to the typical device indicators, such as low battery alerts.

This paper is organized as follows. First we start by giving a brief review of the state of the art followed by detailing the architecture of the emotional devices. Next, the study design is explained in detail. After that the results of the experiment are shown followed by a discussion thereof. Finally, the paper is concluded with the main findings from our evaluation.

2 Related Work

Affective computing studies what triggers the users frustration and anxiety and tries to eliminate that. For instance, [16] demonstrated that in many cases the computer user's feel frustrated while dealing with it. However, after designing a system that detects user frustration and adapt accordingly, the users reported that the frustration was reduced.

Researchers explored the usage of affective computing to enhance user experience [21, 15]. [17] presents a new approach where computer wearables can be

[4] https://www.webpagefx.com/blog/wp-content/uploads/2016/08/how-many-devices-will-you-use-in-your-life.png

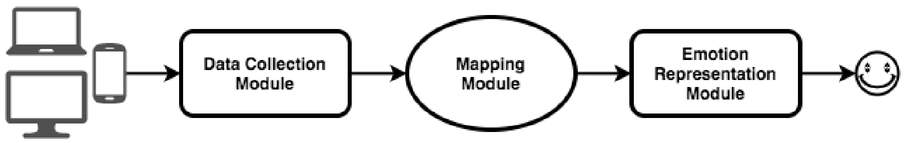

Fig. 1. Architecture of the Artificial Emotions Simulator

used side by side with the questionnaires to know who does a human feel or to know if he/she is saying there honest opinions.

There are different techniques to represent emotions, ranging from simulation of human-like emotions to abstracted representations of emotions. The Kobian humanoid robot presented in [24] exhibits facial and body expressions.[3] claims that machines that can express emotions can have a great impact on users and can affect their decisions.

In [14] and [22] colors were used as an abstracted representation of emotions. The basic human emotions were mapped to colors enabling the expression of human-like emotions suing simple means. The issue in this approach is the fact that although some colors are commonly associated with specific emotions, most of them are not. There are huge cultural and background factors that come in play when dealing with meanings of colors.

Popular emotion representation tool is emojis. In [9, 10] they reported that emojis is a deeper way of communication between people and can have different interpretations based on the sender and receiver. More than 92 % of the internet users use emojis to express themselves. In addition, emojis are sometimes easier than the commonly used languages as it is in some way multilingual. This is why emojis were finally chosen as the means of emotion representation of the presented system.

There are many different factors that affect the computer or mobile device. For instance [23] showed that constant WIFI usage can have a great impact on battery life. For instance, if the downloads are scheduled the battery would not be consumed in a short time and the CPU usage would not increase. Furthermore, [19, 11] declares the CPU usage, battery and memory usage as the most important measures of efficiency of applications, mobiles and computers.

Emotions can have a great role in decision making. There are different representations of emotions and their basic set. [18] includes eight basic emotions: anger, disgust, fear, joy, sadness, surprise, acceptance and anticipation. [4] presents six basic emotions consisting of a subset of the ones presented in [18]; namely all without acceptance and anticipation. Finally, [6] presents a recent study based on advanced technology to study emotions. The work tried to further narrow down the emotions defined in [4] to the most basic emotions. Facial recognition tools were used to try and extract the most basic ones. This further narrowed down the set to only four basic emotions: joy, sadness, surprise/fear and disgust/anger by combining surprise with fear and anger with disgust.

For the purposes of our work the narrowed down set of the four emotions was used to not overwhelm the user. Another concern in the study of emotions is the their trigger. In [13] it is stated that the human brain's activity increases as it senses or generates emotions.

In[18] states that neuro-biological theory proves that the decision making process is mainly driven by emotions. Of particular interest is [2] which found that computers triggered empathetic emotions in humans just like other humans would.

To the best of our knowledge, no tools mapping computer and phone usage data to artificial emotions exist. However, there are various tool that collect and present the usage parameters to the user in a direct way [19, 11, 5].

3 Emotional Companion

Emotional Companion is an artificial emotions simulator. Its architecture is designed in a simple manner. This is to ensure efficiency while using it without depleting the important device resources. This was the main concern in the design. Also, to ensure its portability, the system was implemented on different platforms as proof of concept. All three existing versions, Linux, Windows and Android-based, have almost the same architecture.

The simulator consists of two main components as well as a processing component, as illustrated in Figure 2. The usage data collection module records battery status, temperature as well as CPU and memory usage. This data can be seen represented in plain alpha-numerics whenever the task-manager view of the application is opened. The mapping module consists of equations that translate the usage data to emotions. The equations were chosen based on user questionnaires to choose the most mappings most intuitive to the users. The parameters illustrating the final used mappings can be found in Table 1.

Emotion	Battery	Temp.	CPU	Usage Intervals
Happy	High	Low	< 50	$<$ 5min
Neutral	Moderate	Low	< 50	$<$ 5min
Surprise	-	-	> 50	$<$ 2sec
Angry	Low	High	> 85	-

Table 1. Parameters of Mapping Emotions to Operation Data

The usage interval represents the interval between keyboard strokes and mouse clicks and movement. The device experiences surprise if the CPU usage rises to greater than 50% in a short time interval or if the usage interval decreases to less than 2 seconds. anger if any of the three shown parameters (battery, temperature or CPU) reach the value shown in Table 1.

The emotions representation module takes the emotions resulting from the mapping module and displays them as the device's own using **emoji**-based emotions. Where the emoji-based representation associates the different chosen emotions to their existing emoji counterparts. The emojis appear as a small circle in the any screen corner chosen by the user. The main concern in all the choices was to make it as non-intrusive and as integrated as possible. Also, any glaring pop-ups or constant nagging to the user was avoided to prevent from distracting the user. The main inspiration for this was to learn from Microsoft Office's Clippy; the now deprecated office assistant of many Microsoft Office applications from 1997 till 2004. According to [20], annoying and distracting characters are one of that main causes that make people detest or stop using similar agents.

4 Study

To investigate the influence of the generated emotions by *Emotional Companion* on user's usage, awareness and adaptiveness to their devices' state. In other words, would users actually respond to the needs of their devices if they report human-like emotion, we conducted a user study with the aim to investigate the behavioral change of humans towards their devices when they show their needs as emotions instead of as numbers.

4.1 Design and Apparatus

We applied a repeated-measures design, where all participants were exposed to all conditions. We studied the effect of *Emotional Companion* on the the response rate of the users to their devices in case they requiring charging or a break. For the baseline, we collected the data when the participants where using their devices regularly.

In our study, we deployed *Emotional Companion* on the participants.

4.2 Participants and Procedure

We recruited 15 participants (1 female) with age range 18 to 44 ($Mean = 23.2, SD = 2.35$) using university mailing lists. Participants were students of different majors ranging from computer science to management and university staff.

In our study we compared the the battery and CPU usage values with and without the addition of simulated emotion to the computer. The aim was to see if by changing the way the computer shows its status, the status itself would be attended to quickly and thus improved on the long run.

None of the participants had any previous experience with *Emotional Companion*. After arriving in the lab, participants filled in their demographics and signed a consent form and received an explanation of the purpose of the study.

Baseline Data Collection First, we installed an application to collect the regular usage data. The application starts automatically in the background as long as the devices are running. The application automatically tracks the needed statistics about the device usage; namely battery and CPU usage. Only these two factors were considered during the experiment to limit the number of variables in the experiment and thus have a more severe and well-defined test. No intervention is required from the user at this phase. The aim of the pretest is to give insight on the regular usage patterns of the user and the general state of the device. It is measured if the device often crashes or operates on constant high CPU percentage. It also measures if the battery is being stained by always being depleted before recharging. These statistics are automatically sent from the devices to be stored by consent from the participants. This task spans over two weeks.

***Emotional Companion* Data Collection** Next, after two weeks, we re-invited participants collect the baseline data and to install *Emotional Companion* on their devices. They are given a second application which is similar to the first one with only one addition: emotional display.

The participants are asked to use their computers as they always would and check if the emotions expressed by their devices triggers them to do any actions. They should only perform an action if they feel they want to. The application now displays a small emoji in the screen corner preferred by the user representing its current mood i.e. internal state. The same metrics as in the pretest are collected from the computer and automatically stored. The participants use their devices with the emotion simulator for another two weeks.

Post Task Questionnaire After finalizing both phases of data collection, the participants are presented with a questionnaire to investigate their general feelings towards the application and experiment they undertook. The questionnaire consisted of fourteen questions ranging from basic personal information to whether or not the application was likable. This was done because subjective evaluation relating to the user experience should be considered alongside the objective evaluation. The aim of any tool is aiding the user and providing an enjoyable experience. This gives important insight into whether we are on the right track and what could potentially be changed.

5 Results

The data collected from the study is compared using statistical analysis. We used Null hypothesis significance testing (NHTS) to test whether introducing the simulated computer emotions via *Emotional Companion*, produces no change in the usage behavior and awareness as well as Cohen's d, as shown in Table 2.

Moreover, the feedback from the questionnaire of the participants was analyzed. The questionnaire consisted of 14 questions asking the participants how

	p	d
CPU	0.14	0.42
Battery	< 0.001	0.35

Table 2. Results of the NHTS and Cohen's d for the CPU and Battery usage

they felt about the experiment and the device emotions simulator they tried. Table 3 illustrates the results of the questionnaire.

Question	Result
Rating of application without emotions	3.5/5
Rating of application with emotions	4.5/5
Continuation of using the application	4.3/5
Recommend-ability of application	4.6/5
Acceptance of conflicting emotions (device/user)	4.3/5
Change of user's feeling towards device	4.27/5
Happiness rating while using 2nd application	4.6/5
Suitability of emojis for representation	4.6/5

Table 3. Post Task Questionnaire Results

6 Discussion

The experiment produced two different results, that will be each separately discussed. The experiment was divided into two parts: the pre- and post-test to ensure its internal validity. Then, each of the two variables being tested was analyzed independently to get clean unambiguous results.

In case of the battery usage, the t-test proved that having the device convey its needs as emotions showed significant changes in the user's behavior. This is probably the case as plugging in the battery is usually ingredient till the last minute due to concentration in the task at hand or simply laziness. In case the users are doing something important, they probably will not stop it even if the computer showed its emotions. In the second case of laziness, the user could be triggered to respond to the needs of the device if it relates more to it. So, in the case of the battery the strong statistical result produced can be seen as evidence that the wider aim of the experiment was fulfilled. This is because it initially showed significant behavioral change in the participants when introducing the simulated emotions.

In case of the CPU usage, the t-test showed that the results of the experiment were insignificant. There are many reasons for this that will be discussed below:

1. The CPU usage does not variate as often as the battery does. The battery usage follows a repeating pattern of depletion and recharge. In contrast, the

CPU is usually operating at a steady rate and only spikes on occasion making it harder to detect through the statistical analysis.
2. The state and age of the devices used in the experiment severely affect the results of the CPU usage, as they prevent the CPU from being overworked.
3. The nature of the work done on the computer and thus the occupation of the participants has a huge impact on the results. The heavy computer users running multiple computationally expensive tasks will have strained computers with always high CPU usage. This is why the future experiment setup should handle different participant types separately.
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