Emotional Well-Being in Smart Environments: An Experiment with EEG

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ABSTRACT

Well-being in smart environments refers to the mental, physiological and emotional states of people passing through environments where sensors, actuators and computers are intertwined with everyday tasks. In that context, well-being must be measurable and, to some extent, susceptible to external influence within the short time-spans that people spend in those environments. Continuing our previous studies, we evaluate an experiment for well-being measurement and control, introducing EEG observations in the experiment. EEG, as an immediate and objective proxy of one's mental, physiological and emotional state, provides ground truth for comparisons between sensors in the smart environment. We concentrate on the test subject's emotional state, observed by way of comparing changes in the alpha frequency power levels in the left and right frontal cortical areas, respectively corresponding to positive and negative emotions. The results show that our experimental set-up induces significant changes in the test subject's emotional state, paving the way for further studies on influencing personal well-being.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous computing**; **Empirical studies in ubiquitous and mobile computing**; *Empirical studies in HCI*.

KEYWORDS

well-being; sensoring; measurement; smart environment; EEG; ICA; affective computing

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1 INTRODUCTION

Smart environments, such as smart homes, smart cities and smart offices, are environments where computers are linked to everyday settings and commonplace tasks, with smart devices continuously working to make the lives of the people passing through those environments more comfortable [7]. To achieve this, the environment needs sensors, actuators, displays, and computational elements, connected via continuous networks [10, 24].

Well-being is widely considered a key vertical for the expected ubiquitous wireless intelligence in the 5G and beyond networks [1, 5, 19]. In the context of smart environments, well-being refers to a multi-faceted characteristic of an individual, measurable and, to an extent, controllable within the short time span the individual spends in those environments. Lovén et al. [17] states well-being as a latent feature of an individual, manifesting as her immediate mental, physical and emotional states. Further, a desirable state of well-being is characterized by a flow state of mind, low levels of stress, and a balance between negative and positive affect.

A sensored, controlled environment featuring game-play provides a good proxy for a smart environment, offering a setting for studying how the well-being of an individual may change while performing tasks of varying difficulty and with occasional interruptions [12]. Indeed, Cowley et al. [8] and Shon at al. [23] showed that engagement with computer games may cause changes in a user's state of flow, stress and emotion. While these can be measured with non-physiological signals like speech, facial expressions [4, 20], or body gestures, the observations may be affected by the social and cultural background of the person [15, 16]. In contrast, physiological signals are more robust and thus offer a direct method for measuring flow, stress and emotion.

EEG is a brain monitoring technique that records electrical activity in the brain, providing information on mental activities and emotional states [21]. In more detail, an EEG signal, measured by an electrode placed on the scalp, tracks small changes in the voltage fluctuations of the brain cortex, resulting from ionic current within the neurons of the brain [18]. The EEG frequency bands have a correlation with emotional stimulation [22], providing a reliable method for tracking the emotional states of an individual. Indeed, since EEG responds to emotional stimuli better than other biological signals, it is the most popular method for emotion recognition [21].

Our earlier work proposed an experimental design for assessing the three aspects of well-being, that is, stress, flow and affect. The design was based on game-play, introducing a number of phases and interruptions aimed at inducing changes in the stress, flow and affect of a test subject, as well as a number of both wearable and external sensor for tracking the induced changes. Further, the study analysed the stress levels induced by the experiment in a group of test subjects, measured by a wearable ring-sensor tracking skin conductivity. The results indicated that the test structure was indeed reflected by the observations, with significant correlation in the changes of stress and the experiment.

In this study, we introduce EEG measurement in the experiment, providing a ground truth for further comparisons between wearable and video sensors. We concentrate on affect, and analyse variation in the emotional states of the test subject by comparing the relative alpha frequency power levels on the left and right hemispheres of human brain. Furthermore, we provide some guidelines to improve the test setting based in our processing and analysis of the EEG data.

In summary, the novel contributions of this article are as follows:

(1) We find significant agreement with the emotions of the test subjects and the experiment structure, further justifying the experimental design.
(2) We find that interruptions during tasks requiring heavy concentration lead to negative emotions. Further, the results suggest that the difficulty of a task at hand is not related to short-term emotional response.
(3) We iterate the lessons learned during the EEG experiment, providing best practices for further experiments.

2 MATERIALS AND METHODS

2.1 Experimental Design

Continuing our earlier work, the experimental design is based on game-play[1], disturbed by a number of interruptions introduced by the researchers [12]. The experiment is conducted in a quiet room, equipped with a large LED screen. Two laptops are used, with one for operating the EmotivPro software (for EEG measurements), and the other one for controlling the computer game by a researcher. The game is presented to the subject in the large screen, and a mouse is given for interacting. Two cameras are used, one in front of the subject, capturing the face and upper body, and the second right behind the researchers, capturing the whole scene. Two researchers are present in the experiment, both situated behind the subject. One researcher instructs the test subject, monitoring the sensors and adjusting the game settings, while the other collects user feedback with queries.

Subjects. Fourteen healthy volunteer subjects, both male and female, participate in the study. Most of the volunteers are researchers from different fields from the University of Oulu, Finland, between the age of 20 and 45 years and with different nationalities. All of the subjects are right-handed, with no history of mental illness, brain injury, nor psychiatric disorders. The researchers explain the subjects the purpose of the experiment and the procedures. Moreover, one of the researchers give them a questionnaire form in to fill in their age, gender, whether they have had any head, brain injury, neuralgic or chronic diseases, and, finally, a have them sign a written consent.

Devices. EEG signals are measured from the scalp with a 32 channel Emotiv EPOC Flex wireless EEG device. EEG recording channels are located according to the international 10-20 system, with data recorded at a sampling frequency of 128Hz. Also, a video recording system captures the head and body gestures and the facial expressions of the test subject.

Procedure. The experiment consists of six main phases from 0 to 5. In phase 0, the subject is allowed to play freely to get familiar with the game. In phase 1, game-play is interrupted with a Skype call. In phase 2, the game is again interrupted by external control over the mouse. In phase 3 and 4, the subjects are challenged to win the game, while rigging the game difficulty settings heavily against them. Finally, phase 5 has the subjects play an easy game with high chances of winning. The phases are further detailed in Table 1.

Table 1: Experiment phasing. (Table adapted from one by Halkola et al. [12].)

Phase	Time (min)	Comments
0	3-5	easy game, warm-up
1	8-10	easy game, Skype call while playing
2	8-10	easy game, external control of mouse
3	5-10	difficult game, losing
4	3-8	difficult game, losing
5	5-10	easy game, winning, cool-off

Synchronization. A mobile phone is used for EEG data time synchronization. On the onset of an event, the mobile phone is tilted on a specific EEG measurement electrode, creating a marker in the EEG signal while also increasing a counter shown in the phone screen. Additionally, the video recording assists in time synchronization. Further, the raw EEG data is augmented with markers with the EmotivPRO software.

2.2 Preprocessing

We filter the EEG data with a bandpass filter in the frequency range of 4.0–45.0 Hz, and apply blind source separation by independent component analysis (ICA) [6], implemented as the python library MNE-Python [11], to remove the ocular and other physiological artifacts that were mixed into the recorded EEG signal. Finally, we segment the EEG signals into ten seconds time frames.

2.3 Feature Extraction

EEG feature extraction refers to obtaining useful information from the brain signal to characterize the emotional states of the test subjects. Indeed, the human brain processes different emotions in different areas. The left frontal cortical area is responsible of processing all positive emotions, while negative emotions are associated with the right frontal cortical area [9]. The brain cortical activation is negatively correlated with the alpha band (8–12 Hz) activity, which means a decrease of alpha band power in the left hemisphere relative to the right one reflects a positive emotion and, vice versa, a decrease in the right hemisphere relative to the left one reflects a negative emotion. [2, 3, 13, 21].

We use alpha band (8-13Hz) power ($\mu V^2/Hz$), extracting Welch periodograms [25] on the F3 (located in the frontal left hemisphere) and F4 (located in the frontal right hemisphere) EEG recording

[1]https://www.bubbleshooter.net/original-bubble-shooter/

Table 2: *Before* and *after* time frames, used to calculate the contrasts C_i.

Phase	Before	After
1	10s in the beginning of phase 0	10s after interrupt
2	10s in the beginning of phase 0	10s after interrupt
3	10s in the beginning of phase 0	10s before end of Phase 3
4	10s in the beginning of phase 0	10s before end of Phase 4
5	10s in the beginning of phase 0	10s before end of Phase 5

channels. We then first calculate the lateralized power level ratio between the F3 and F4 channels, and then the temporal changes in ratio, comparing certain 10 second intervals to a baseline interval recorded in the beginning of the test.

Following [2], the lateralized power ratios P for alpha band are calculated as

$$P = \frac{L - R}{L + R},$$

where L and R correspond to left and right hemisphere alpha band power, as measured respectively by the F3 and F4 channels. A high resulting P thus indicates a negative emotional response, while a lower one indicates a positive emotional response.

2.4 Aggregation and Significance Testing

The final results are the robust pseudo-medians [14] of the power ratios P of each test subject in each phase, estimated with a non-parametric 95% confidence interval [14]. We use the robust paired Wilcoxon signed rank exact test [26], which does not require normality, to test the significance of the contrasts C_i,

$$C_i = P_{i_a} - P_{i_b}.$$

Here, $i \in \{1, 2, 3, 4, 5\}$ corresponds to the phases in the experiment, and b and a indicate the *before* and *after* time frames, as listed in Table 2.

3 RESULTS AND DISCUSSION

Fig. 1 demonstrates the changes in the emotions of the test subjects during the experimental phases, as measured by the laterilized power band ratio P for each test subject (gray lines), and the pseudo-median of all subjects (blue line), along with its 95% confidence band (red area). Higher values indicate more negative emotions.

The results indicate a neutral phase 0, followed by elevated negative emotions in phase 1 to 2, to be levelled off in phases 3, 4 and 5. The results are further detailed in Table 3, along with significance values for contrasts to power ratios in phase 0.

There is a lot of variation in the emotional response of the different test subjects during phases 1 and 2. This may be the result of varying reactions to the interruptions. Some of the subjects, for example, were visibly amused by the interruptions, as indicated also by the low values for some individuals (gray lines) appearing in Fig. 1 for phases 1 and 2. Overall, however, elevated negative emotions in phases 1 and 2 indicate that interruptions during game-play, a task requiring concentration, irritates the test subjects.

There is no evidence of the difficulty of the given task, as tested in phases 3–5, affecting the positive or negative emotions of the test subjects. Instead, phases 3–5 may have more of an effect on the

Table 3: Pseudo-median of the lateralized power ratio P in the value of alpha power for each phase, along with significance of the contrast to phase 0. Green background with asterisk marks significance.

Phase	P_i	C_i p-value
1	10.8	0.035∗
2	10.7	0.020∗
3	0.69	0.76
4	-0.32	0.90
5	-0.079	0.71

flow or stress levels of the test subject, as suggested by Halkola et al. [12]. This is further supported by the very low variation across test subjects in phases 3–5. Alternatively, however, the lack of evidence may be caused by the relatively small sample size (14 test subjects).

4 LESSONS LEARNED

As part of the evaluation of our test environment, we include some remarks and best practices on how the experiment should be conducted to ensure best results, concentrating on the observation and analysis of EEG measurements.

First, prepare to test more subjects than required for statistical power. For example, we had to discard some EEG tests results entirely as the amount of artifacts made them infeasible for analysis.

Second, to improve the EEG analysis, we recommend capturing each test subject's reference level for EEG. The reference level can be measured by including a phase in the beginning of each experiment where the test subject closes her eyes and sits quiet.

Finally, although our approach for synchronization has been successful, some adjustments could simplify the process. For instance, the electrode where the mobile phone would be tilted, thus indicating an event in such as the change of phase, could be defined

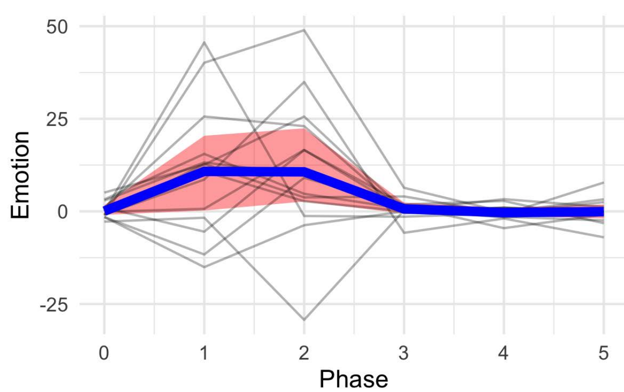

Figure 1: Emotion during experiment, measured by the laterilized alpha band power ratio between the left (F3) and right (F4) alpha band channels. Higher values indicate more negative emotions. Individual observations are the gray lines, the blue line marks the pseudo median of the ratio, and the red area indicates the 95% confidence interval.

clearly in advance. In the presented setting, we used inadvertently a subset of electrodes of the same area. As a result, the affected electrode had to be manually looked up for each event.

5 CONCLUSION

We expanded our earlier experiment on measuring well-being in smart environments by introducing an analysis of test subject emotion with EEG. We used the change in the alpha frequency power level for left and right front cortical area, respectively corresponding to negative and positive emotions.

The result showed that external interruptions during game-play significantly increased the negative emotions experienced by the test subject. Task difficulty, on the other hand, was not correlated with changes in emotions of the test subject. Finally, we described the lessons learned during the experiment.

In further studies, we plan to increase the number of test subjects, expand the EEG analysis to cover also stress and flow, and introduce control of the smart environment to observe how well-being can be influenced.

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