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Measuring archetypal experiences with physiological sensors

Leonid Ivonin, Huang-Ming Chang, Wei Chen, and Matthias Rauterberg

The instincts and innate behaviors that form the collective unconscious can be recognized by a computer using physiological sensors.

Research in human computer interaction (HCI) has made remarkable progress, moving from simple pointing or touch-based interfaces to more advanced interaction paradigms powered by physiological computing, in which physiological data serves as input to the computer system.[1] Computing interfaces take measurements—such as heart rate and skin conductance—which can be analyzed to measure cognitive[2] and affective[3] aspects of user activities. Research in psychology[4,5] and neuroscience[6] has provided evidence that people are not aware of their own cognitive processes, and are not able to report accurately on them.[7] Thus, developing computer systems that can report on cognitive processes is of interest.

A considerable part of human experience is tied to the unconscious. The unconscious experience can be indirectly assessed by methods developed in psychophysiology,[8] which are similar to measurements employed in physiological computing. Carl Jung described the content of the unconscious as 'archetypes' or 'pre-existent forms.' Archetypes are close analogies to instincts, which are impersonal, inherited traits that shape and motivate human behavior without consciousness. Computer recognition of archetypal experiences remains a largely unexplored area of HCI. [9,10] Having a model of unconscious behaviors would enable novel interactions, and it would allow a HCI system to respond to changes in the unconscious levels of human experience.

We examined the possibility of sensing and distinguishing between various archetypal experiences based on the analysis of physiological signals. First, we used film clips to elicit eight archetypal experiences (anima, animus, hero-departure, hero-initiation, hero-return, mentor, mother, and shadow) in our test subjects. Film clips are effective in capturing the attention

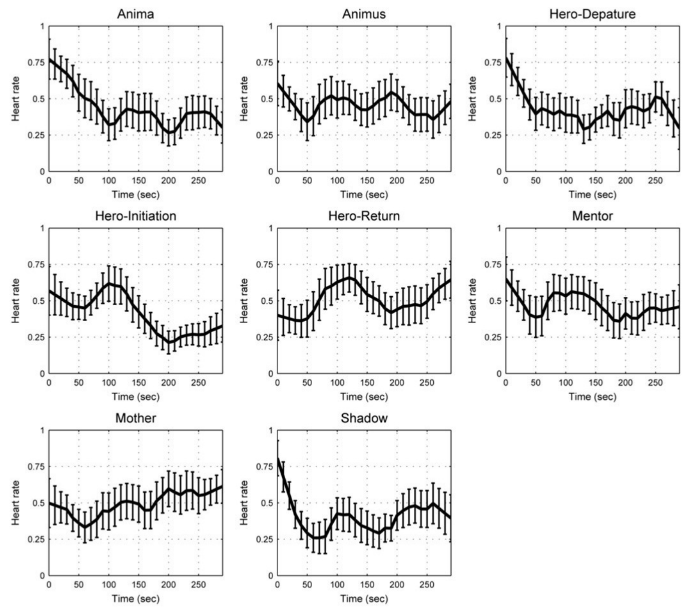

Figure 1. *The dynamic patterns of heart rate responses (mean values and 95% confidence intervals) of participants during various archetypal experiences, as elicited through film clips.*

of individuals and have a relatively high degree of ecological validity, meaning that they can effectively resemble real life scenarios.[11] We outfitted the subject with Shimmer^{TM}wearable wireless sensors[12] to measure his or her electrocardiography (ECG) and skin conductance. For respiration and skin temperature measurements, we used a Refa amplifier from TMSI BV in combination with an inductive respiration belt and a temperature sensor. We then normalized physiological signals by subtracting the baseline values from the data corresponding to stimuli presentation (see Figure 1).

We chose feature-based classification to analyze the physiological data. This involves the calculation of features that describe time series, and then the use of conventional classification

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methods for static data. It is advantageous to reduce the number of features as much as possible in order to develop a model that is computationally efficient and robust.[13] We transformed 158 features into 7 components with a dimension reduction technique. Once time sequences of physiological data were transformed into feature vectors, we built predictive models based on three types of classifiers: K-nearest neighbor (kNN), naïve Bayes, and linear discriminant analysis (LDA). In order to ensure that a classification algorithm was not trained and tested on the same dataset, we employed a leave-one-out cross-validation technique.

The model we built with the kNN method was able to correctly classify 74% of the instances. The mentor archetype had the lowest true positive rate. The anima archetype had both the highest false positive and true positive rates. The overall accuracy of the model we obtained with the naïve Bayes classifier was 79.5%. Finally, we used the LDA classifier to build a prediction model. The Box's M test showed a highly non-significant result ($p = 0.527$), meaning that the assumption of equity of covariance matrixes was not violated. Thus, we could proceed to the interpretation of the outcome of the classification. The model with the LDA classifier had a classification rate of 79.5%, which was identical to the one achieved with the naïve Bayes method.

Overall, the experimental findings indicate a positive relationship between the physiological signals of subjects and the induced archetypes. Moreover, we were able to train prediction models, which differentiated between eight archetypes with an accuracy of up to 79.5%. The experimental design ensured that the results can be generalized to practical HCI scenarios.

Our future work will primarily focus on refining the classification models and developing a tool for user experience evaluation that integrates physiological sensors and the obtained algorithms. Moreover, we plan to conduct additional studies to confirm the generalizability of our findings.

Author Information

Leonid Ivonin, Huang-Ming Chang, Wei Chen, and Matthias Rauterberg
Eindhoven University of Technology
Eindhoven, Netherlands

Leonid Ivonin is a PhD candidate affiliated with Eindhoven University of Technology and the Polytechnic University of Catalonia.

Huang-Ming Chang is a PhD candidate in the Erasmus Mundus doctoral program. His PhD project aims at evaluating emotional experiences.

Wei Chen is an assistant professor. Her research interests include sensor systems for ambient intelligent design, healthcare system design using wearable sensors, wireless body area networks, and smart environments.

Matthias Rauterberg is full professor for Interactive Systems Design at department Industrial Design. He has over 400 publications in the areas of human computer interaction, entertainment and cultural computing, as well as interaction design.

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