The Potentials of Neuroscience Methods for Business Process Modeling Tools

Maria Shitkova, Justus Holler, Jörg Becker, University of Münster - ERCIS

Corresponding author: maria.shitkova@ercis.uni-muenster.de

Neuroscience methods have already been recognized as a powerful mechanism for human-computer interaction research (Riedl et al. 2010). These methods provide instruments for detecting the user emotions based on the reactions of human nervous system. In this paper we explore the potentials of integrating neuroscience methods for detecting emotions in business process modeling (BPM).

Strong emotions, such as stress, can on the one hand negatively affect the work performance (Laborde et al. 2013; Lazarus 2000), and on the other hand can also be an indicator of the user attitude to the information system she is using at the moment (Albert and Tullis 2013). Thus we see two possible application scenarios for the case of BPM tools. The first scenario is closely connected to the decrease in work performance and quality of work results, when the user is experiencing strong emotions. Thus if it is possible to detect user emotions when she is creating process models, it will be also possible to *predict the quality of created BPM models* (S1) (Heide et al. 2014). The second scenario presupposes that user emotions may be caused by the computer program she is interacting with at the moment (e.g. inefficient or unsatisfactory program functions often cause stress (Albert and Tullis 2013)). Tracking user emotions may help to identify potential problems in the software and thus *continuously improve BPM tool usability* (S2). We further present a concept of integrating neuroscience methods into a BPM tool for detecting user emotions and discuss both application scenarios in detail.

The proposed concept is based on the BPM tool icebricks (Becker et al. 2013). The tool provides a possibility to model and analyse business process models for arbitrary business domains. The existing icebricks architecture can be described as a simple process model repository together with a web-based modeling environment and user profile. In order to incorporate the neuroscience methods into the BPM tool we extend this architecture with neuro-sensors and an analytical assessment mechanism for detecting user emotional condition as shown in Figure 1. User profile and process model repository will also be extended to store user emotions data in order to satisfy the requirements of the concept.

To detect user emotions particular measurement devices have to be used. Two main groups of measurement tools exist in neuroscience: brain-imaging tools and psychophysiological tools, also called lightweight solutions (Loos et al. 2010). The first group of the tools tracks the activity of different brain areas using electroencephalography (EEG), functional magnetic resonance imaging (fMRI), positron emission tomography (PET) and other rather complicated devices. These tools are difficult to integrate into "real-world" information systems (IS) applications, because they are not flexible with respect to time (when can participants use the system?) and space (where can participants use the system?) and thus using this kind of measurement devices leads to an artificial working environment. The second group of tools is the oldest and simplest techniques to measure somatic states by capturing indicators closely related to the nervous system (e.g. facial emotional response (EMG), skin conductance response (SCR) or eye tracking) (Loos et al. 2010). This second group can more easily be integrated or applied in IS areas.

As the proposed concept requires an emotion measurement tool, which seamlessly integrates into the working environment, does not distract the user from performing the tasks or create any discomfort, the usage of lightweight solutions is a good trade-off between accurateness and effort (Adam et al. 2011). Following the studies (Adam et al. 2011; Albert and Tullis 2013; Kreibig 2010) the measures of heart rate (HR), heart rate variability (HRV) and skin conductance level (SCL) were chosen to detect the user emotional arousal. Under stress the HR and SCL indicators tend to increase, while HRV decreases.

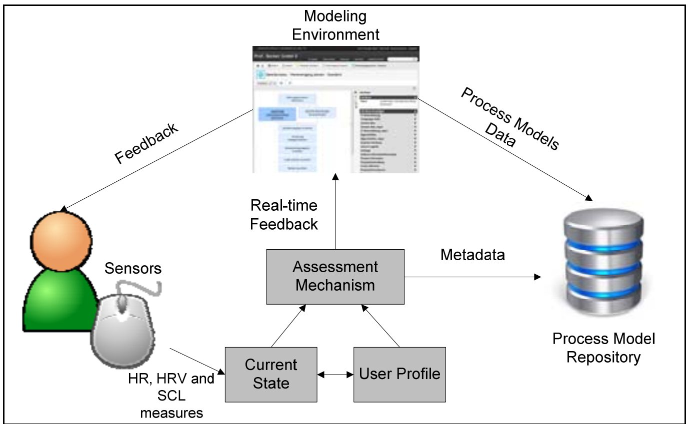

Figure 1. Architecture

A Shark-fin Mouse, proposed by (Christy and Kuncheva 2013) is a possible alternative to the standard HR and SCL monitors, which normally has to be attached to the fingers, wrist or chest, which might cause inconvenience to the user. It is a fully functional computer mouse, which streams pulse and skin conductance data in real-time. We propose this kind of device to be used in our concept.

In order to define the current emotional state of the user, the user profile has to be extended with baseline and threshold values of HR, HRV and SCL. The baseline values define the normal emotional state for the user, while the threshold values reflect the levels of HR, HRV and SCL at which the user is expected to be in a strong emotional state and to potentially produce work results of poor quality. The initial baseline values can be measured when creating the user profile. The threshold values can initially be set to the baseline values and then adjusted as the user interacts with the system.

The assessment mechanism detects the current emotional state of the user and classifies the state as either influencing the quality of the work results or not. The current emotional state of the user contains the aggregated measures of HR, HRV and SCL. Due to the usage of sensors embedded in a computer mouse the HR, HRV and SCL measures can only be collected when the user touches the mouse. This results in the following sets of measures $HR=\{HR_0,\dots,HR_n\}$, $HRV=\{HRV_0,\dots,HRV_n\}$ and $SCL=\{SCL_0,\dots,SCL_n\}$. The indexes $\{0, \dots, n\}$ represent the intervals when the measurement took place (e.g. each time the user touches the mouse), HR_i, HRV_i and SCL_i are the average heart rate, heart rate variability and skin conductance level values taken during one of the several measuring intervals.

The process model repository is extended to keep the trace of the users' actions and emotion measurement data during to the session along with the process models data created. The trace of user actions and emotion measurement data serve as metadata for the process models. All the entries are synchronized using timestamp values and can later be used for usability evaluation (S2).

The assessment mechanism then compares the current emotional state to the user's threshold values in order to define the presence of strong emotions (e.g. stress). The assessment results are also stored as metadata together with the created models and can be later used for predicting the quality of created models (S1).

As presented above we have defined two potential scenarios for using the neuroscience measures in BPM tools, which we discuss in the following part of the paper.

S1 – predicting quality of process models (Heide et al. 2014).

The quality of business process models created in a modelling project is of high importance and has to be constantly monitored and assured during all phases of the project (Becker et al. 2011). Emotions such as stress affect general work performance of the user, and thus also the results of process modeling (Laborde et al. 2013; Lazarus 2000). The major problem is however, that as soon as the process model is stored in the process repository, the emotional context is lost and it becomes difficult to detect the quality a posteriori. The artefact is then used without reflexion, which may lead to misinterpretation. Thus the task of storing the emotional data together with the artefact is crucial for quality prediction.

By using assessment mechanism to detect the presence of stress, the quality indicator *(QI)* can be set automatically for any created or updated process model by using the following rule:

$$\text{if } \max_{i=0,n} HR_i \geq HR_{TR} \text{ or } \min_{i=0,n} HRV_i \leq HRV_{TR} \text{ or } \max_{i=0,n} SCL_i \geq SCL_{TR}$$

then *QI="Potentially Poor"*, else *QI="Potentially Good"*,

where $\max_{i=0,n} HR_i$, $\min_{i=0,n} HRV_i$ *and* $\max_{i=0,n} SCL_i$, are the "worst case" measures of heart rate, heart rate variability and skin conductance level for the current session. Basically each time when the "worst case" measures exceed the threshold value it is assumed that the user has experienced stress during work and the work results are considered to be potentially of poor quality. The "worst case" scenario is used as reference value in order to minimize the number of false positive predictions.

The quality indicator can then be used for moderation of created process models. If the QI is set to "Potentially Poor" the process model will be hidden from other BPM tool users and has to be checked by the author or by his or her colleague or supervisor. Thus the quality of the models inside the BPM repository is constantly monitored and it is assured that the overall quality of models available for the users is always sufficient.

In case the moderation takes place, the threshold values are refined afterwards. If the quality was predicted wrong by the assessment mechanism, new threshold values of HR, HRV and SCL are set to the averages between the old threshold values and the "worst case" current state measures. Thus over time the system learns the user emotional indicators and the threshold values are adjusted to correctly predict the quality.

S2 –continuous usability evaluation of the BPM tool

Stress is also seen as an indicator of poor usability of the tool the user is interacting with, and thus can be used in usability testing (Albert and Tullis 2013). In the concept proposed in this paper the BPM tool is tracking the user actions and saves the respective data as part of the

process models in the database together with the emotion indicators – HR, HRV and SCL.
This data can then be analysed in detail in order to identify the functionality of the tool, which needs improvement. By looking at the highest HR and SCL and lowest HRV values, it can be concluded that the particular functionality used at this moment is not fully understandable by the user or difficult to use, thus causing stress. This functionality can then be evaluated in detail by conducting additional usability tests and gathering quantitative (performance) and qualitative (satisfaction) usability metrics.

Traditional usability testing approaches usually are carrying out experiments with test participants, gather performance data and conduct interviews or surveys. In case of BPM tools this can be rather time consuming, because of the complex functionality of BPM tools. In the proposed approach the neuroscience mechanisms are seamlessly integrated into the working environment and provide the usability assessment data while the user interacts with the system. Thus it is possible to continuously assess the usability level of the application and improve the problematic functionality. After a certain amount of time the users will eventually interact with all the functions in the tool and thus the complete functionality will be tested for usability.

Other possible application scenarios

Another application scenario might be providing live feedback for the user on the current emotional state. The modeling environment should be extended with an emotional indicator, which warns the user when she is potentially stressed. With the help of the indicator the user's attention is called to his current emotional state. Based on the automatic and constant feedback, the user can decide to take a break or to postpone the knowledge work and may switch to activities less affected by the emotional condition. This improves the work results of the user in the short term and strengthens the user's awareness for emotions, thus preventing such illnesses as burnout, in the long term.

The proposed concept of integration of neuroscience methods into BPM tools provides us with the possibility of fostering the overall quality of process models stored in the repository and continuously test and improve the usability of the tool.

One of the drawbacks of the proposed conceptual solution is the limited number of emotional measures (only HR, HRV and SCL) and rather simple rules for detecting the presence of strong emotions. It is also difficult to recognize exact emotions (positive or negative) as different mental events can produce nearly identical physical responses (Kreibig 2010). We believe there is a possibility to extend the concept by incorporating further measurement methods, e.g. pupil dilations (Albert and Tullis 2013), and more sophisticated assessment mechanisms in order to better detect the presence of stress.
In future work we plan to prototypically implement the proposed concept and conduct a set of experiments to prove its applicability.

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