

# Exploring the potential of neurophysiological measures for user-adaptive visualization

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**Abstract.** User-adaptive visualization aims to adapt visualized information to the needs and characteristics of the individual user. Current approaches deploy user personality factors, user behavior and preferences, and visual scanning behavior to achieve this goal. We argue that neurophysiological data provide valuable additional input for user-adaptive visualization systems since they contain a wealth of objective information about user characteristics. The combination of neurophysiological data with other information like eye movement data can significantly improve system reliability by reducing the inherent uncertainty in the interpretation of the user data. Moreover, neurophysiological data can be obtained continuously and unobtrusively without disturbing the interaction of the user with the system.

**Keywords:** visualization, user adaptation, neurophysiology

## 1 Introduction

User-adaptive visualization is a novel approach to adapt an information visualization to individual user differences. For example, it can mean adapting the visualization to general (and typically static) user traits such as speed of perceptual processing or user expertise. In this case, adaptation to the user happens only once or a limited number of times. Adaption can also occur more or less continuously, e.g. when the visualization is adapted to the current mental and/or cognitive state of the user (attention, emotion), or to the characteristics of the user-visualization interaction (such as history of user actions).

One of the current research questions in user-adaptive visualization is which individual characteristics can be used as ‘input’ for adaptation. In this paper we explore the possibilities to adapt visualizations to the continuously changing mental state of the user as can be estimated by (neuro)physiological variables such as heart rate and brain signals. The advantages of using neurophysiological variables are that they provide a continuous, online measure, and do not involve potentially distorted or subjective post-hoc judgment. Also, ongoing miniaturization and development of wireless sensing techniques will allow minimal user interference in the near future.

In this paper, we first provide a short overview of related work in user-adaptive visualization, focusing on the individual characteristics that are typically employed and how these are gathered. Next, we examine the state of the

art in neurophysiological measurement. Finally, we provide ideas on how these neurophysiological measures could be used to adapt the visualization, i.e. what characteristics of the visualization can be adapted and how. This includes ideas on how neurophysiological measures can complement other commonly used measures of individual characteristics, such as eye gaze data.

## 2 Adapting to the user

A variety of factors can be used to adapt a visualization to an individual user. In this section, we briefly review the current state of research in user-adaptive visualization, focusing on *which* individual differences can be used to personalize a given visualization for a particular user. We distinguish differences in personality factors, user actions and preferences, and visual scanning behavior.

Previous work [1, 2] has found that personality factors (locus of control, extraversion and neuroticism) influence performance with different visualization types. Also, several cognitive abilities correlate with various aspects of visualizations. For example, spatial ability correlates with comprehension of (3D) information visualizations [3]. Toker et al. [4] show that perceptual speed (also see [5]), verbal working memory, visual working memory and user expertise have a significant effect on task efficiency, user preference and ease of use of different visualization types. Toker et al. [6] show that perceptual speed and verbal working memory also have a significant effect on eye-gaze behavior when viewing a visualization. The authors suggest that adaptive interventions can be driven by these individual characteristics, for example, by giving more emphasis to certain elements of the visualization (e.g., more emphasis on text for users scoring low on verbal working memory). We note that personality and cognitive abilities are typically assessed with computer-based or paper-and-pencil tasks and questionnaires [3–6], or self-reports [4]. However, self-reports are potentially unreliable, as several memory errors can undermine their accuracy [7]. Also, they are susceptible to social desirability biases. Steichen et al. [8, 9] address this problem by using eye gaze to infer these cognitive abilities. Finally, we note that adapting to these relatively static user traits is less suitable for interactive or continuous adaption of the visualization.

Another commonly used approach, more suited continuous adaption of the visualization, is to adapt to user actions and (implied or explicitly given) preferences (e.g. [10–12]). This information can be used to build a user model, which can be updated over time based on new information, i.e. dynamic. An example of a dynamic model is one that learns from expressed user dislike of a visualization [13]. However, information on these actions and (dis)likes does not reveal *why* these occurred, as they do not give information on the user's (mental) state.

The use of eye gaze measures can provide information on user state. For example, Steichen et al. [8, 9] use eye gaze to predict the user's task. Also, they use eye gaze to infer cognitive abilities such as perceptual speed, visual working memory and verbal working memory. As noted above, these cognitive abilities have a significant effect on the use of different visualization types. Conati et

al. [14] investigate the possibilities of using eye gaze to detect when the user needs an adapted visualization. For example, duration of a fixation can indicate complexity, pupil dilation may indicate cognitive load and eye gaze data can be used to determine areas that the user has not looked at. Also, eye gaze can reveal informative patterns such as repeated scanning of the same area in a visualization [15]. In general, for analyzing data generated by an eye-tracker, several metrics are potentially informative: number of fixations (a large number of fixations generally implies a less efficient search [16], or a large number of fixations on a particular area of the screen can be indicative of high interest in that area), fixation duration (long fixation duration often means the user has difficulty extracting information [16]), number of saccades (more saccades indicate a larger amount of visual search), scanpath metrics (such as length, duration and convex hull [17]), or saccade direction changes (a direction change larger than 90 degrees could imply that the user's goals have changed or the user interface is not the way the user expected [18]). Eye gaze measures can be extracted online and continuously without interrupting the user. However, there are several problems associated with eye gaze measures, such as how to define a fixation, how to account for errors in gaze location and how to handle scanning interruptions [15].

Summarizing, current approaches to user adaptive visualizations are based on differences in personality factors, user actions and preferences, and visual scanning behavior. However, since measures of personality factors are inherently unreliable and biased, and since eye movements need additional information for a correct interpretation, additional sources of information are needed to correctly estimate a user's state of mind. In the next section we argue that this information can partly be obtained from neurophysiological measures.

### 3 Neurophysiological measures

In this section we will show which neurophysiological measures can provide objective information about the mental and cognitive characteristics of users.

A multitude of neurophysiological variables can be measured and analyzed more or less continuously and non-invasively in an office environment. The advantages of using neurophysiological variables are that they are a continuous, online measure, and do not involve potentially distorted or subjective post-hoc judgment. Previous work has already suggested that user-state monitoring is the next potential breakthrough in the use brain-computer interfaces [19]. Examples include electrical brain activity as measured at the scalp (electroencephalography or EEG), oxygen-bound hemoglobin in the brain (near-infrared spectroscopy or NIRS), a combination of EEG and NIRS [20], cardiovascular measures (e.g. heart rate and blood pressure), respiratory measures (e.g. respiration rate) and electrodermal measures (electrical conductance of the skin which varies with sweat excretion).

Non-invasive portable equipment that records brain signals (EEG and NIRS) can only do so from the surface of the brain (the cortex). The signals themselves,

electrical activity and the amount of oxygen-bound hemoglobin, are weakened and smeared out by the tissue lying between the sensor and the origin of the signal, and the signals themselves are rather indirect measures of what the brain actually is doing. Still, they can provide us with potentially useful information. Much of the cognitive and sensory functions are localized in the cortex. Roughly speaking, the frontal area is involved in cognitive processing, the area at the back of the brain in vision, auditory processing is at the sides of the brain and touch is at the upper part. This localization knowledge can be combined with general indicators of brain activity or inhibition. For EEG, the power of frequencies around 12Hz (alpha band) indicate idling [21] or inhibition [22] of the recorded part of the brain. For NIRS, a relatively large amount of oxygenated blood generally corresponds to brain activity. For example, experiments on workload indeed indicate that frontal alpha activity [20, 23, 24] and oxygenated hemoglobin increases with task difficulty. For a more detailed overview of the usefulness of brain-based indices for effort, vigilance, workload and engagement see [25].

Another common type of measurement extracted from EEG besides power in frequency bands are event-related potentials (ERPs). These are the peaks and valleys as observed in averaged EEG traces that are locked to an external event, such as the onset of the presentation of an image. The P300 is a peak occurring 300 ms (or somewhat later) after the presentation of a stimulus that attracts special attention. This special attention can be because it either pops out with respect to previous and subsequent stimuli (e.g. [26]), because of inherent meaning (e.g. one's own name in between others names [27]) or because the stimulus is one that the individual is asked to consciously attended to [28]. Error related potentials [29–32] are ERPs associated with the onset of making a mistake that is realized to be a mistake or with the onset of an unexpected outcome of an action.

The correlates of cognitive and attentional processes in EEG as described above cannot be observed in raw data with the naked eye. While classical EEG studies make use of averaging over many trials to visualize and determine effects, applied neuroscientific studies (for which it is crucial to extract information from one individual over a relatively short time period) commonly use classification techniques (e.g. linear discriminant analyses, support vector machines). Van Gerven et al. [33] give an overview of using classification techniques in brain-computer interfaces. In short, EEG is recorded while an individual experiences the states of interest at known time intervals (e.g. low and high workload, or image of interest present or not). With these labeled EEG data a classification model is trained. The trained model can then classify new unseen data into the trained categories. Usually, models are personalized, though work is ongoing to create models that generalize over participants [34].

Whereas cognitive and perceptual processing occur mostly at the cortex, emotional processing occurs mostly in the center areas of the brain. Therefore, to track emotions, other (physiological) measures are needed. For example, an increase in skin conductance (i.e., sweating) and a decrease of high-frequency heart rate variability are associated with stress or arousal [35–38]. Kreibig [39]

gives an extensive review of physiological correlates of different basic types of emotion such as anger and disgust. However, it is important to note that physiology does not correspond one-to-one to different emotions, but stimuli and context matter. Alternatively, emotional valence and arousal could be derived from facial expressions (facial expression analysis software is available).

#### 4 Neurophysiological data - novel opportunities for visual adaptation

In the previous sections, we have shown that neurophysiological data can be employed to learn more about user characteristics. Naturally, a follow-up question is how this can be linked to adaptation of the visualization. In other words, when we know more about the user, what aspects of the visualization can be adapted such that the user is supported better. In general, aspects of the visualization that can be adapted to the user include:

- which data is shown,
- how the data is shown (visualization type, e.g. [5]),
- how the visualization is parameterized (how data attributes map to visual attributes, e.g., size and color)
- how the data is laid out spatially (e.g., [10])
- what portion of the data is shown (e.g., zoom and filter settings),
- which details of the data are shown,
- which elements of the visualization are given more visual emphasis (suggested by [6, 14]), and
- help provided to the user.

As noted, neurophysiological measures can be used to estimate workload and stress/arousal. This information about the user could be used to adapt the visualization. For example, if stress levels and workload are high, the level of detail of the visualization, or the amount of data shown could be reduced. Also, more help could be provided when workload is high.

While we are not aware of studies on the use of (neuro)physiological measures in adaptive visualization, several studies have examined the use of information as revealed by eye movements. Eye movements can also reflect mental state and, as mentioned previously, share the advantages of (neuro)physiological measures. Neurophysiological measures can be used to complement eye tracking data. In general, we note that a *combination* of information sources (neurophysiological, eye tracking or also facial expressions or body posture [40]) will likely prove most effective. For example, while a fixation on a certain area of the visualization can mean the user is interested in that area, it can also mean that the user does not understand something in that area or that (s)he is simply staring. With neurophysiological measures, these different states can be differentiated better. Conversely, eye tracking can reveal information that neurophysiological measures might not so easily capture. For example, point of gaze is a measure that is most easily captured using an eye tracker. Another example of how combining

neurophysiological measures with eye-tracking could lead to more insight into current user behavior is differentiation between searching and exploring behavior. Many gaze shifts in combination with hardly any long fixations can imply that a person is searching for an item [18]. If this is found to be paired with a high workload as indicated by EEG signals, it may imply that the user cannot find what he/she is looking for. If paired with a low workload the user may just be (casually) exploring the visualization.

As for ERP measures, we note that in the vast majority of ERP studies, experimental participants do not move their eyes at the time that the stimuli of interest are presented, so that perception onset is fixed and EEG artifacts caused by eye movements are limited. This conflicts with every day (visualization) behavior where individuals look around freely. However, when EEG is examined following eye fixation onset rather than image onset, similar ERPs can be distinguished [41]. This offers the possibility to deduct from EEG and eye movements where the user is looking when he/she realized that there was mistake or an unexpected outcome. This information can then be used to detect anomaly or error, to present a pop-up help query, or to automatically highlight (or tag) the area where this happened so the user can easily return to it later.

Because the neurophysiological measures discussed in this paper are continuous the effect of such adaptations can be measured on-the-fly, and different adaptations can be experimented with. Combined with an adaptive (or learning) user model this can lead to highly personalized visualizations.

## 5 Conclusion

User-adaptive visualization aims to adapt visualized information to the needs and characteristics of the individual user. Current approaches typically deploy user personality factors, user behavior and preferences, and visual scanning behavior to achieve this goal.

We have shown that neurophysiological measures can provide information about the mental state of an individual. Challenges include noise and interpretation difficulties caused by body movements and speech. These can cause ‘actual’ disturbances to the signal as well as confounds (e.g. in a high workload situation individuals move more than when workload is low, causing higher heart rate due to movement rather than mental workload). However, since visualizations are often used in a relatively quiet environment, with relatively stationary users, there is minimal risk of noise and confounds in the neurophysiological data. We therefore believe that user-adaptive visualizations are a relatively good case for exploring the potential neurophysiological measures.

Finally, we note that robust, user friendly and high quality measurement equipment needs to be developed, especially to reliably and easily record EEG. Impressive progress is being made [42, 43] and first user friendly EEG measurement equipment is on the market. Also, we note that some methods that are more time- and resource-demanding, such as fMRI, whilst unsuitable for adapting visualizations online could be used for the evaluation of visualization.

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