Seeing how you're looking - Using Real-Time Eye Gaze Data for User-Adaptive Visualization

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1 Introduction

In the field of cognitive and perceptual psychology, the use of eye tracking has long been established as a suitable means for analyzing user attention patterns in information processing tasks [11]. More recently, the fields of human-computer interaction and information visualization have similarly started to use eye-tracking technology to investigate trends and differences in user attention patterns and cognitive processing, e.g. for different interfaces/visualization types [13][7], task types (e.g. reading vs. mathematical reasoning) [8], or user abilities (e.g. cognitive abilities [16], expertise [12]). Researchers have also started to use machine-learning techniques on gaze data to predict, for example, user intents [3], cognitive processes [5][14], or student learning [10][4]. Similarly, in our own work [15], we have shown that we can predict a number of visualization task types and user characteristics using simple machine learning techniques on a broad set of eye gaze measures and statistics.

However, these studies have generally only attempted to gain insights or generate models using *off-line* processes. In terms of actually using eye tracking in *real-time* systems, most early research has focused on designing gaze-directed interaction, i.e. using gaze data as a direct input to control a system [9]. Such interaction techniques are now also appearing in mainstream, commercial applications, such as TVs [2] or mobile phones [1]. Researchers have recently started to build systems that go beyond simple gaze-direction, by performing dynamic adaptations to basic gaze patterns (e.g. providing feedback to 'unattentive' students looking away from the screen [6]). However, such systems typically only use basic eye fixation counts/lengths, rather than the full spectrum of eye gaze features explored in the machine-learning experiments described above. They are hence quite limited in terms of adaptation potential. In the next section, we present a system that bridges this gap by providing a real-time, feature-rich eye-gaze analysis service that can be leveraged by user-adaptive systems.

2 Real-Time Gaze Analysis Service

As shown in Figure 1, our service consists of a web server application that continuously receives raw gaze data from an eye tracker. When a client application (which may or may not be located on the same machine as the web server and/or eye-tracker) places a request for analysis, the server calculates real-time statistics, either starting from a specific start time (set previously by the client application), or for a specific time window (as specified in the server configuration file, e.g. the last 10 seconds).

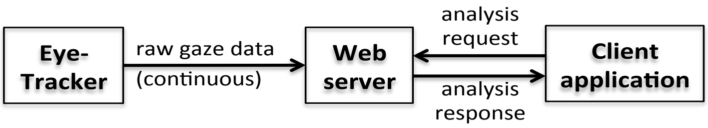

Figure 1. Real-time eye-tracking architecture

The web server application integrates a feature-rich eye-gaze analysis module, which is capable of calculating numerous summative statistics. Example features that can be requested by client applications include a user's fixation-rate (i.e. number of fixations per second), mean absolute saccade angles (i.e. angles of the trajectory between two fixations), proportionate amount of time in an *Area of Interest* (AOI) (the location of AOIs is set in a configuration file), transitions between AOIs, etc. (see [15] for a more detailed description of all features).

There are two main advantages of this architecture over previous systems described in section 1. First of all, the web service has been designed to be application-independent, and may therefore be reused for different application domains and purposes. Requests and responses are handled using a simple REST model, which can be easily integrated into any network-connected application. This also means that client applications do not have to run on the same machine as the eye-tracker (see section 3, use case 1). Secondly, in contrast to previous gaze-based adaptive systems presented in section 1, the service integrates a broad range of eye gaze statistics and is therefore capable of driving adaptive systems that are based on feature-rich classification techniques (an example of this is shown in section 3, use case 3).

3 Use-Cases of User-Adaptive Visualization

There are a number of use-case scenarios where the above architecture can be leveraged for real-time adaptive applications. In particular, since visual scanning and processing are fundamental components of working with any form of visualizations (and in fact the only components for non-interactive visualizations), eye tracking may be particularly useful in this field. Below is a quick summary of three scenarios that we have devised in our own research on adaptive, gaze-based visualizations.

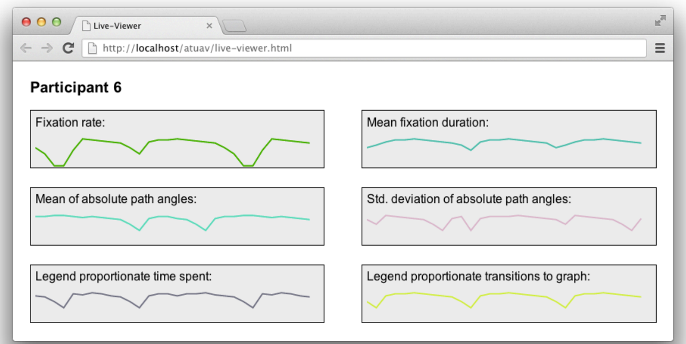

Figure 2. Real-time visualization of eye gaze statistics

Use-Case 1: Real-Time Gaze Visualization

The first use-case is to simply display the different analysis values in a real-time visualization. Figure 2 provides a sample screenshot of a 'spark lines' visualization that we have implemented to showcase the underlying service's real-time processing capabilities. As an end-user 'looks' at a screen displayed on the eye-tracker, this live statistics visualization can be viewed, for example, by a remote experimenter in order to see the real-time changes of the end-user's eye gaze. This setup may be useful for system pilot-testing, real-time gaze analysis, or Wizard-of-Oz-type studies.

Use-Case 2: Gaze-based triggers in Visualization Experiments

A second application scenario is to use simple gaze-based trigger rules to provide basic forms of adaptation. For example, in a recent study we wanted to force users to first read the experimental task question before viewing the corresponding visualization. We used simple fixation-based rules that specified that the 'number of fixations' in the 'text area of interest' had to be above a certain threshold before triggering the visualization display. This use case resembles simple gaze-based adaptation as presented in section 1, however, it is worth noting again that a client application can choose from a much larger array of features to be used for triggering actions.

Use-Case 3: User-Adaptive Visualization

The most sophisticated use-case scenario combines the gaze-based service with rich classification and intervention techniques to predict and adapt to individual user traits and states (e.g., task, individual user characteristics, transient states). In order to implement such a system, the client application (e.g. an adaptive visualization system) requests the full set of eye gaze measures over a specific period of time (e.g. last 10 seconds). Secondly, the measures are run through a previously trained classifier to predict a user's task and/or characteristics (as shown in our previous work [15]). Lastly, the system provides an adaptive intervention that is suitable for the predicted context. Interventions could, for example, consist of reference lines (to facilitate comparisons), bolding (to highlight important parts of the visualization), or de-emphasizing unimportant information (to help users who are overwhelmed by visual clutter).

4 Conclusions and Road Ahead

This paper has presented a quick overview of an architecture that is capable of providing real-time eye gaze statistics to adaptive systems. The service has been fully implemented and has already been used for the development of real-time gaze statistic visualizations (use-case 1), as well as an application that uses simple gaze-based triggers (use-case 2). The next steps include the integration of an end-to-end user-adaptive visualization system, which combines this real-time eye-tracking service with a machine-learning-based classifier and an adaptive visualization intervention framework (use-case 3).

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