Computers in Human Behavior 63 (2016) 796–804

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

Using eye movement data to infer human behavioral intentions

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ARTICLE INFO

Article history:
Received 5 August 2015
Received in revised form
26 May 2016
Accepted 12 June 2016
Available online 21 June 2016

Keywords:
Human behavioral intentions
Intention inference
Intention classification
Eye movement
Natural user interface

ABSTRACT

Behavior-directed intentions can be revealed by certain biological signals that precede behaviors. This study used eye movement data to infer human behavioral intentions. Participants were asked to view pictures while operating under different intentions, which necessitated cognitive search and affective appraisal. Intentions regarding the pictures were non-specific or specific, specific intentions were cognitive or affective, and affective intentions were to evaluate either the positive or negative emotions expressed by the individuals depicted. The affective task group made more fixations and had a larger average pupil size than the cognitive task group. The positive appreciation group made more and shorter fixations, on average, than the negative appreciation group. However, support vector machine algorithms revealed low classification accuracy. This was due to large inter-individual variance and psychological factors underlying intentions. We demonstrated improvement in classification accuracy using individual repeated measures data, which helped infer participants' self-selected intentions.

1. Introduction

In recent years, natural user interfaces (NUIs) have been developed and shown to be useful for a wide range of devices, including TVs, PCs, video game consoles, and smart phones (Kim, 2012; Kwak, 2013; Liu & Zordan, 2011; Oh, 2013a,b). NUIs are intuitive human computer interfaces based on a person's natural behaviors (Kim, 2012). While it is convenient to point with the fingers rather than using a mouse, or using eye gaze rather than typing, it is problematic if a NUI incorrectly understands human intentions. For example, the "smart pause" technology implemented in smart phones allows a user to pause a video clip simply by looking away from the display. However, this operation is undesirable if the user looks away from the display to avoid seeing unpleasant scenes. That is, this technology, which uses biophysical measurements of the viewer, does not fully take into account the user's requirements in different situations. Thus, for proper performance, the system needs to detect a user's intentions in a specific situation. The aim of the present study was to infer human behavior-directed intentions using biological signals.

1.1. The relationship between intentions and biological signals

Intentions can be defined as ideas, needs, and a willingness to undertake a certain behavior (Gollwitzer, 1993). The theory of planned behavior (Ajzen, 1985) states that intentions shape behaviors. A person is regarded as having an intention to engage in a behavior if s/he desires a specific result, and believes that behavior will produce the result (Park & Cho, 2014). Intentions can be revealed by biological signals prior to a behavior's occurrence (Han & Pereira, 2013; Kim, Kim, Yoon, & Lee, 2007). Furthermore, intentions are future-directed and strong predictors of behavior (Han & Pereira, 2013; Malle, Moses, & Baldwin, 2001; Sooniste, Granhag, Knieps, & Vrij, 2013). Ajzen (1991) revealed that behaviors could be predicted from intentions, with considerable accuracy. Additionally, several studies (Ajzen & Driver, 1992; Bolmont, Cacioppo, & Cacioppo, 2014; Lee, Park, Lee, Chang, & Kwak, 2015; Watters, 1989) concerning the ability to predict behavior from intentions have been conducted.

1.1.1. Measurement of intention

Psychological concepts such as intentions are hard to directly measure. To infer a person's behavior-directed intentions, it is necessary to measure biological signals (e.g., eye-movements). Umemoto, Yamamoto, Nakamura, and Tanaka (2012) proposed a system that used a person's fixation counts to increase the

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http://dx.doi.org/10.1016/j.chb.2016.06.016
0747-5632/

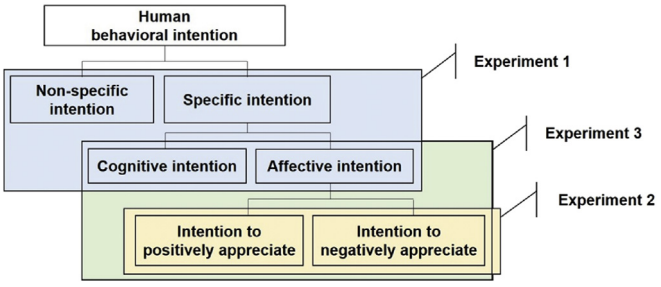

Fig. 1. Classification of intentions for each experiment.

efficiency of information retrieval. Jang, Lee, Mallipeddi, Kwak, and Lee (2013) designed a user-intention search-monitoring system using fixation counts, fixation length, pupil size variation, the gradient of pupil size variation, eye-blink variation data, and a probability classifier model. This monitoring system offers appropriate information or services by actively responding to a user's intentions. Cutrell and Guan (2007) used an eye-tracking methodology to explore the effects of changes in the presentation of Web search results. These can significantly improve performance in information retrieval. Finally, Buscher, Cutrell, and Morris (2009) introduced a method for mapping gaze data to predict visual attention for Web pages. Accordingly, using a high-performance camera and software for measuring eye movements has become common, and eye-tracking techniques have become a parsimonious way of measuring intentions (Umemoto et al., 2012).

1.1.2. Classification of intentions

Intentions can be classified by their targeted action. In the present study, we define a state with no specific intention as *non-specific intention*; otherwise, the state includes a *specific intention*. We are unaware of prior studies that have classified intentions by using eye-movements. Most studies of intention have focused on information retrieval associated with Web searches. In classic information-retrieval studies, people typically search for information based on their needs (Shneiderman, Byrd, & Croft, 1997). Broder (2002) classified Web queries into three categories, reflecting a person's intentions, as follows: informational, navigational, and transactional. A user survey showed that Web queries usually reflect an informational intention, followed by transactional, and navigational intentions. Jansen, Booth, and Spink (2008) also showed that more than 80% of Web queries have an underlying informational intention. Informational intentions can be classified based on Wilson's model of information-seeking behavior (Wilson, 1981). According to this model, informational needs are qualitatively similar to basic human needs, and may be divided into cognitive, affective, and physiological types. Based on these findings, human intentions can be classified as non-specific or specific. Specific intentions can be further classified as cognitive or affective (see Experiment 1).

Ekman's six basic emotions (sadness, anger, disgust, surprise, pleasure, and fear) have been used as the basis for designing emotion-processing models for human-robot interactions. Ortony, Clore, and Collins (1990) divided twelve emotions into two groups. The first group consisted of pleasure, hope, relaxation, pride, appreciation, and love, and the second included pain, fear, disappointment, regret, anger, and hatred. These can be generally defined as positive and negative emotions, respectively (Kim, Jeong, Lee, Lee, & Noh, 2004). Ishii et al. (2005) found significant differences in eye-movement data for individuals viewing positive and negative emotional pictures. Regarding the cortical underpinnings, Schmidt and Trainor (2001) found that positive emotions are processed in the left frontal lobe and negative emotions in the right frontal lobe. Accordingly, in the present study, we divided affective intentions regarding images into two groups; intentions to positively appreciate the image and to negatively appreciate it (see Experiment 2).

1.1.3. Inference of intentions

Researchers have attempted to infer intentions by using the biological signals transmitted by individuals, and individuals' attitudes. Lee, Chun, Kim, and Chung (1999) inferred intentions of a person with motor control impairments by using head and pupil movement patterns, in order to propose interfaces for operating electric wheelchairs and assistive devices. A hands-free wireless and intelligent multimedia communications device called "eyeCan," was developed by Samsung Electronics to enable paralyzed individuals who only have control over their pupil movements to use computers (Kang et al., 2012). Doshi and Trivedi (2009) were able to predict drivers' lane change intentions using eye and head movement patterns. Finally, Choi (2013) designed a situational awareness system for detecting abnormal behavioral intentions from CCTV images.

1.2. Paintings and eye movements

In the study of aesthetic emotions, eye movements have been used to investigate perception, cognition, and assessment of artwork (Locher, 2006; Nodine & Krupinski, 2003). Fixations and saccades are used to gather information from a painting (Locher, 2006). A saccade is a quick eye movement between two phases of a fixation. Fixation is the process of maintaining visual gaze toward a single location (e.g., fixations occur when the eyes rest on a part of a painting for a short period; Ponce & Mayer, 2014). Eye movements denote a pause for collecting information about a particular area of a picture, indicating that a person is paying attention to that spot (Goldstein, 2007). Eye-movement patterns are influenced by

Fig. 2. Stimuli of Experiment 1. (A) *The Nest Egg* by Abbott Fuller Graves, 1910. (B) *Paying the Harvesters* by Léon Augustin L'hermitte, 1882. (C) *The Country Children* by Theodore Gerard, 1875. (D) *Flirtatious Afternoon in the Drawing Room* by Ladislaus Bakalowicz, 1833.