Towards gaze-supported emotion-enhanced travel experience logging

Yiwei Wang, Martin Raubal, Peter Kiefer

Institute of Cartography and Geoinformation, ETH Zurich, Switzerland
{yiwewang, mraubal, pekiefer}@ethz.ch

Abstract. Experience logging helps people to create a digital archive of their daily activities. As technologies advance, modern devices make it easier to include various elements into travel logs, including emotions. We propose research on a novel topic utilizing eye tracking features and physiological signals to detect travelers' emotions in the wild and to develop a visualization prototype for travel experience logs.

Keywords. Eye tracking, emotion, experience logging

1. Introduction

Experience logging is a way to record daily life activities. Its purpose is to work as a memory aid and help users better reflect upon past events (Belimpasakis et al. 2009). The idea of digitally recording life experience dates back to the 1940s when Bush (1945) imagined a man in the future wearing a camera on his forehead and taking pictures of valuable moments. Nowadays, Location-Based Services (LBS) (Huang et al. 2018) enable users to record travel logs which typically include trajectories, text, and media (Huang et al. 2015).

Although emotions play a major role for a memorable travel experience (Moyle et al. 2019), they are rarely included in current LBS for travel logging. Understanding travelers' emotions is an important challenge, as emotions can indicate travelers' behavior and motivations behind their activities (Goossens 2000). Outside of the tourism research field, emotion itself can also provide us with additional information about how people perceive their surroundings, enabling us to adapt the environment to people's needs (Gartner 2010, Resch et al. 2015).

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Self-report survey is one of the most popular methods to log emotions (Chiou et al. 2011). It is simple and straightforward but sometimes lacks precision (Li et al. 2015). Complementary, eye tracking (Lim et al. 2020) and other physiological sensors (Hadinejad et al. 2019) have been suggested for emotion recognition - sensors which have also gained increasing interest in the LBS literature recently (Anagnostopoulos et al. 2017, Kwok et al. 2019).

However, research on using eye tracking and physiological signals for emotion-enhanced experience logging in LBS is still missing. In this work-in-progress paper, we outline research on detecting emotions during traveling using a multimodal approach and developing a visualization prototype for travel experience logs. We tackle the following research questions:

- Q1: Does a combination of eye tracking and physiological signals enable us to detect emotions more accurately than each of them alone?
- Q2: How can we detect a traveler's emotions in the wild?
- Q3: How to design a visualization for emotion-enhanced travel experience logging that can help users recall critical events?

2. Background

2.1. Experience logging

Early applications of experience logging focus on providing a supplement to memory with video and audio including Remembrance Agent (Rhodes & Starner 1996). These systems capture events passively without user interventions. But they often require the user to manually select or annotate events subsequently.

Blum et al. (2006) developed the inSense system, with an algorithm using location and other features to classify events in real time. When a possible interesting moment is detected, the system takes a picture and records a short audio clip, which can be a memory aid for the users.

Kalnikaite et al. (2010) investigated how experience logging could help us remember past events. Participants were asked to use a camera for two weeks to capture their daily activities, and later do a recall test. Results show that locational data supports inference of past events whereas images are associated with directly recalling events.

2.2. Emotion detection

Two types of features are dominant in emotion detection: physiological signals and eye tracking. Emotions are believed to be associated with autonomic nervous system physiological responses (Levenson 2014), thus they can be detected by changes in physiological signals. Commonly used physiological signals include electroencephalography, electrodermal activity, electrocardiography, blood volume pulse, and skin temperature (Bota et al. 2019). These signals can be easily recorded with wearable sensors or devices. Similarly, eye movements allow us to infer about a user's attention and could possibly reveal emotions associated with certain moments (Lim et al. 2020).

Most of these emotion detection studies were performed in the lab with different types of stimuli including video, audio, image, and text (Badshah et al. 2017, Deng & Ren 2021). However, few studies perform emotion detection in an outdoor environment. This has left a research gap among the current studies.

3. Research outline and challenges

We propose research on using eye tracking features and physiological signals to detect emotions evoked during travelling and developing a travel experience log visualization prototype, using emotion as a context. It can be divided into three steps as shown in *Figure 1*.

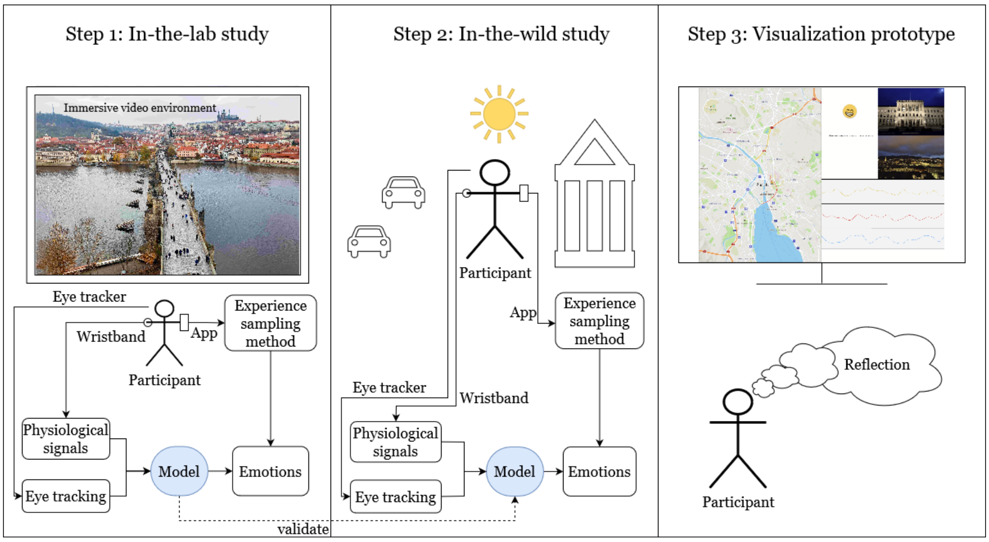

Figure 1: Project overview

First, a controlled lab study will be conducted to test if a multimodal approach can detect emotions more accurately. During the study, participants will be shown video clips of a traveler's pedestrian egocentric perspective in an immersive video environment (Schröder et al. 2023). An eye tracker for collecting eye movement data and a wristband for collecting physiological signals will be used. Experience sampling method will be used to complement ground truth emotions using the circumplex model of affect (Russell 1980) after each video. Machine learning models will be trained for emotion detection. In step 2, a study in the wild will be performed to validate and improve the trained model, with nearly the same experiment setting except a longer time interval for sampling emotions. Finally, a visualization prototype for travel experience logs will be developed. The traveler's GPS tracks are overlaid on a base map, with emotion annotation generated by the trained model displayed. Users can also input annotations either as a correction or complement. We plan to compare different visualization and interaction methods for this tool.

Several challenges lie within the study part, especially during the in-the-wild study, where illumination could have a significant effect on pupil size. How to distinguish pupil size changes due to emotion or illumination needs to be further studied. This could potentially lead to a context-aware emotion detection model that can adapt itself according to lighting conditions in the wild. The in-the-wild study must also be carefully designed to ensure that different types of emotions are evoked during the travel.

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