Real-time Behavioural Analysis using Google Glass

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Abstract

Lifelogging is a form of pervasive computing that represents a phenomenon whereby people can digitally record their own daily lives in varying amounts of detail, for a variety of purposes. Lifelogging offers huge potential for supporting behaviour change because it can capture the totality of life experience and provide heretofore unknown levels of insight into the real-world activities of the lifelogger. In this paper we present a real-time curated lifelogging prototype that can support real-time behavioural analysis by supporting immediate feedback and intervention to the lifelogger.

1. Introduction

Lifelogging is "a form of pervasive computing, which generates a unified digital record of the totality of an individual's experiences, captured multi-modally through digital sensors and stored permanently as a personal multimedia archive" [1]. Since lifelogging captures a detailed log of life activity [2], it makes an ideal source of data for behavioural analysis. Indeed lifelogging is already employed for various aspects of behavioural analysis, such as sedentary behaviour [3,4], physical activity recognition [5] and diet monitoring [6,7,8]. This is because a lifelog represents the ultimate "black box" of a human's life activities and as such, the potential mining or inferring knowledge about how we live our lives is enormous [2].

In this paper, we present a real-time lifelogging prototype that operates on Google Glass, in conjunction with server-based architecture that mines/monitors the incoming data to organize, structure and present this data. This lifelogging prototype can operate in both automatic (like a Microsoft SenseCam [9]) or curated modes. In automatic mode, Google Glass will capture and upload multi-sensory lifelog data (including images) at fixed periods without user intervention. In curated mode, the user will choose when to capture lifelog data by means of pre-defined gestures such as an eye-blink. The contribution of this work is that we present the first real-time lifelogging prototype for wearable computing devices (Google Glass) that, with the correct event detectors, could be used to support real-time behaviour analysis and intervention, where real-time typically required a number of seconds between capture and feedback.

2. Lifelogging for Behaviour Change.

The relationships between lifestyle behaviours and health outcomes are usually based on self-reported data, which is prone to measurement error. Lifelogging has societal applications in terms of providing better fidelity when measuring the behaviour of groups of individuals in a given population, which helps inform policies for tasks like transport planning, environment understanding, and relationships between lifestyle exposures and disease outcomes. Lifelogging sensors, such as wearable cameras and their associated software tools have developed to the point that they are well-suited to measure physical activity, sedentary behaviour, active travel, and nutrition-related behaviours across populations of users [10]. This work fits into this progression by presenting the next-generation real-time lifelogging tool.

From [10], we know that initial lifelogging for behaviour change studies was achieved using devices such as the Microsoft SenseCam [9], which incorporated a VGA camera with fisheye lens, an accelerometer, a light intensity meter, a thermometer and a passive infra-red (PIR) sensor to detect the presence of people. The SenseCam was worn around the neck using a lanyard and by default, a SenseCam captured a new image about every 40 seconds unless triggered by its sensors to capture an image sooner. Captured data was stored using onboard memory, with capacity for about ten days worth of lifelog data. A full day of wearing of a SenseCam would generate between 3,500 and 4,500 images and could support post-capture analysis (i.e. not in real-time). Aside from the SenseCam, there are other dedicated lifelogging wearable devices on the market also, such as the Narrative Clip and the OMG Autographer; both of these operate in a similar manner to a SenseCam. The ubiquity of smartphones suggests that they could also become a valuable real-time lifelogging device and it was recently shown that a smartphone worn on a lanyard around the neck can provide similar levels of lifelogging effectiveness as a dedicated device such as the SenseCam [11], though also support real-time interventions.

Some specific examples of wearable camera lifelogging tools used by public health researchers and others to help inform policy decisions include the work of Kelly et al. [3] who used wearable cameras to identify self-report error in travel behaviour in both adults and adolescents. Kerr et al. [4] employed an annotation framework to manually categorise fine-detail sedentary behaviours from lifelog data, in order to better identify factors that may be driving such behaviour. Doherty et al. [5] were able to identify sedentary, light, moderate, and vigorous intensity physical activities through a combination of accelerometers and wearable cameras. Reddy et al. [6] was able to identify self-reporting errors in a behaviour study of nutrition using a smartphone running lifelogging software. O'Loughlin et al. [7] and Gemming et al. [8] found that they were able to help participants to identify forgotten calories through using wearable camera images as memory prompts.

However, in these cases there were two important drawbacks. Firstly, the device did not act in real-time, hence it always provided a retrospective review and could never support real-time interventions. Secondly, wearing a phone or a dedicated device such as a SenseCam on a lanyard means that there is significant potential to miss capturing events of interest, which do not by necessity occur directly in front of the wearer. Hence, having a real-time, head-mounted lifelogging platform offers advantages over any of the previously used devices. Integrating SenseCam type functionality (automatic capture of periodic images, coupled with sensor data) into a Google Glass type device results in a new type of lifelogging device, that tracks head movement, but also supports both automatic or triggered capture, along with the potential for real-time interventions. However, in the current pre-release prototype of Google Glass, battery-power restricts the usage to periods of a few hours at a time. In Figure 1, we show the types of photos that can be captured using a Google Glass device.

Figure 1. The image outputs of a real-time lifelogging tool running on Google Glass, showing social activities, driving and food-related activities.

3. A Real-time Lifelogging Platform

The real-time lifelogging prototype presented in this paper is based on two core components, a wearable, head-mounted lifelog capture device (software running on Google Glass) and a server-side application that stores, organises, analyses and presents the lifelog data for multi-modal access (See both sides of Figure 2).

The data captured by the head mounted device can originate from multiple sensors, including visuals, audio, accelerometer, etc. The list is very similar to a smartphone sensor set; as such the findings in [11] can equally apply to the head-mounted device. Data that is captured on the wearable device gets uploaded to the server immediately, or at the next available opportunity (network availability depending), whereupon it undergoes semantic analysis and organization. The data gathering can operate in either an automatic or curated manner. If it is automatic, then the user does not need to do anything to gather content; the device simply logs photos and sensor readings continually (one every minute, though it is configurable) until the user either switches it off, or until the power is drained[1]. The alternative (or parallel) method of capture is the curated data gathering option which uploads every image explicitly taken (along with appropriate sensor data) to the server for analysis. In curated-mode, photos can be taken in any manner that the device allows; in our case, by button press, in-built voice command or blink-to-capture.

On the server, an initial suite of semantic analysis tools are being developed at present that will operate over the data; these include face detectors, eating detectors, sedentary activity detectors and event segmentation tools. Since these detectors run on the server, there are few CPU and power constraints that would limit the types of analytics that could be performed. An overview architecture is shown in Figure 2, which contains two access devices, three semantic detectors (e.g. faces, eating, sedentary activities) and data stores, data and interface handlers.

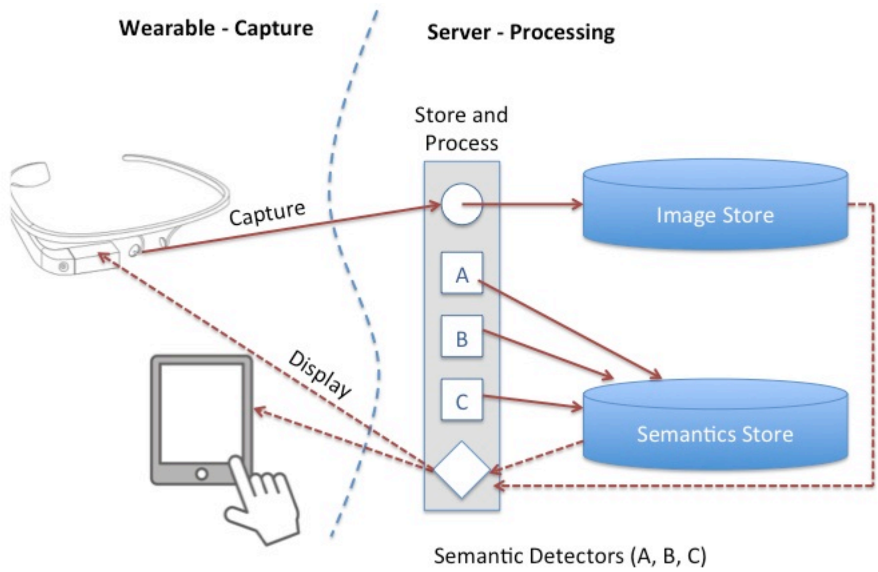

Figure 2. A summary overview of the real-time wearable lifelogging solution.

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[1] Since Google Glass is currently a pre-release prototype, the battery was not designed to support all-day capture, hence the device can only lifelog continually for a matter of hours.

The access to the processed data (semantic data) could be done using many different types of access device. Access could be via a computer or tablet to support reminiscence or retrospection, or it could be on the capture device itself to support real-time interventions and communication. Naturally the interface elements are heavily dependent on the use cases and the modality of the access devices. For real-time interventions using a wearable device such as Google Glass, then the interface should be card based and focus on just the required information at any point in time (e.g. an intervention). For reminiscence or quantified-self style analytics over past life experiences, then a large-screen device that charts, summarise and presents analytics results over the data would be more suitable. Our use-cases below are primarily focused on the reminiscence use cases.

4. Current & Future Work

Given a real-time lifelogging platform that can support retrospective access for reminisce or reflection, as well as real-time interventions, there is enormous potential to deploy and evaluate new types of behaviour chance analytics. Some of the use-cases we see big potential for at present include:

- *Digital Diaries* for personal reminiscence and review. Sellen and Whittaker [12] present a suggestion of the five reasons (5Rs) why people would access lifelog stores. One such reason is to support Reminiscence, which would be a key driver of long-term behaviour change and requires the integration of an effective event segmentation technique to organise the lifelog data into a series of events that take place each day.

- *Diet Monitoring*. Gesture-based capture of food being consumed will allow for diet monitoring applications to be developed that can feedback appropriate messages to the user.

- *Product Knowledge*. Object and logo matching in real-time from the point of view of the buyer would allow for immediate analysis of, and feedback based on, the content being purchased.

- *Lifelong Analytics*. Referencing past life experiences potentially over decades opens up new opportunities for behaviour change analysis and intervention.

Of course, these are only a short list of potential use-cases. In reality, there would be a huge list of potential use cases based on analytics tools that understand the user, their activities and environment. In this early work, we focus on the key beneficial use-case of digital diaries, which provide a source of data for either human or automated analytics to support behaviour change. These digital diaries can be explored by the wearer or a third-party, or could even act as input for a suite of analytics tools as described above.

The lifelogging prototype that we present in this work can support real-time analysis and feedback. It is our conjecture that a wearable, head-mounted lifelogging device meets all the same criteria as presented in [11], but does so more effectively by tracking the user head movements, though currently for limited periods of time due to battery constraints. Consequently, we propose that this prototype could be used to gather detailed lifestyle activity records and therefore has potential to be employed as a means of supporting behaviour change.

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