Public health associations with transportation choices as measured by wearable cameras

Abstract/Overview

As public health researchers we are interested in identifying the opportunities individuals have to engage in active forms of transportation, primarily walking or cycling. Before designing interventions to change travel behaviours, good measurement of existing levels of behaviour, and understanding the determinants driving it is essential. Traditionally health researchers have used large scale travel surveys, but these rely on self-reported behaviour which is limited due to a number of factors. We use wearable cameras, which capture first person point of view images from the perspective of the individual. These cameras help objectively identify the duration, frequency, and mode of journeys taken, and any potential errors inherent in self-report. This may ultimately lead to better understanding of the environments that offer individuals opportunities to engage in more active forms of transportation.

A public health view on travel

Public health is concerned about the health of large population groups, rather than attention focused on individual cases. Geoffrey Rose, a pioneering epidemiologist, has argued that a small change in individual behaviour across a population of individuals will result in less individuals requiring medical treatment over a long period of time. It is acknowledged that such a theory has little perceived benefits for any given individual, but the population benefits can be great. For example in the U.K. the economic consequences of lifestyle choices such as poor diet costs £5.8bn, obesity and overweight £5.1bn, smoking £3.3bn, alcohol £3.3bn, and physical inactivity £0.9bn. The quality of life and social consequences are also significant too.

From a public health perspective, these small changes could include increasing an individual’s walking and cycling journeys. This would contribute to meeting the international guideline amounts of 150 minutes per week of moderate to vigorous exercise. A systematic review of the literature by Ogilvie and colleagues in the British Medical Journal demonstrated that regular walking is significantly associated with reduced risk for all-cause mortality. Walking is one of the safest, most convenient form of physical activity as it is low-impact, low cost and readily accessible, requiring no special skills or equipment. In terms of public health it is an important form of activity because of an unwillingness or inability of many in the population to participate in more vigorous activities. Anderson and colleagues in the Archives of Internal Medicine have shown that cycling, taking into account other factors such as accidents and injuries, is associated with reduced mortality and cardiovascular disease risks.
Health research into travel behaviour is aimed at understanding who is making journeys, how long they take, what modes are used, what routes are taken and why, and what is the context of the journey. Results are used to direct state health and transport departments on policy, funding, future research, and the design and implementation of improved active transport interventions.

**Forms of measuring active travel**

In large travel studies, self-report diaries are used. Individuals are trusted to accurately report their travel behaviour in terms of all journeys taken and also the exact duration they are. However, any self-report or recall method is subject to the usual bias and fallibility of human memory. Some individuals struggle to accurately report information, others may misinterpret the question asked, and others still may try to provide the answer that they assume the researcher would like rather than the truth. For example in the USA 38% of respondents indicated that they met the national physical activity guidelines. When given accelerometers it transpired that only 5% of individuals met these guidelines. Current forms of measurement in travel research such as GPS and accelerometers have strengths, but are unable to provide a clear indication of journey mode.

We concentrate on wearable camera devices, which capture images from a first-person point-of-view. To our knowledge wearable cameras provide the closest match to the accepted gold standard measure of direct observation in health behaviour assessment. Commercial devices are now becoming available such as the Looxie, Memoto, and others. Due to reaching a critical mass in other research areas such as memory rehabilitation, lifelogging, and market research; we use the SenseCam wearable camera. It is worn via a neck-worn lanyard and captures an image approximately every 10-15 seconds when triggered by sensors which log temperature, movement, light, and passive infrared data. Figure 1 shows the SenseCam can capture images of individuals engaging in travel episodes. In previous work in both the American Journal of Preventive Medicine and the International Journal of Behavioural Nutrition and Physical Activity, we have demonstrated that the SenseCam captures as many journeys as are recalled using self-report, such as walking, cycling, driving, underground trains, buses, aeroplanes. Furthermore we have demonstrated that it is a valid methodology to use in larger trials to investigate the error inherent in self-reported travel behaviours.

From an ethical point of view, SenseCam research has some subtle yet fundamental differences to traditional photographic methods of research. Firstly, it generates thousands of images per day and this volume of information could be considered a greater intrusion than traditional methods. Secondly, the wearer often forgets they are wearing the camera and photographs could be captured that they would not purposefully take e.g., visiting the bathroom or using Facebook at work. This is also an intrusion on their privacy. Finally, the first-person point-of-view images capture third parties (from family members to work colleagues to the general public) who will not have been able to provide consent to having their image taken during a research study. As health researchers our work
is directed by principles such as: Respect for autonomy which relates to issues of voluntariness, informed consent, confidentiality, and anonymity; Beneficence which concerns the responsibility to do good; Non-maleficence involves the responsibility to avoid harm; and Justice encompasses the importance of the benefits and burdens of research being distributed equally. Guided by this we produced an ethical framework for SenseCam research that focusses on informed consent from participants, strategies for informing third parties, a review and deletion procedure for participants prior to analysis and privacy of data (scrambling images and secure storage). This Framework is due to be published in the American Journal of Preventive Medicine.

**Processing wearable image data**

Considering that the SenseCam is a useful tool to identify travel related behaviour, the data needs to be processed in an appropriate manner. The SenseCam is capable of capturing up to 2,000 images per participant per day. In our studies thus far we have collected approximately 350 participant days (700k images) and now share the approaches we have used to manage this data.

Previously we automatically segmented the images into different events or activities using an open-source browser made freely available for the research community on http://sensecambrowser.codeplex.com/. This was achieved via looking for changes in activity levels using the on-board accelerometer, as described in a Human Computer Interaction journal in 2012. Such a segmentation algorithm was developed for general purpose approximations of activities individuals were engaged in for self-reflection. However to inform policy makers and other researchers, episodes of travel behaviour must be accurately identified with exact start and end images marked. As a result we display all images of a given day in a scrollable listbox where a researcher can explicitly identify the start/end images of each journey.

Once the individual journeys are identified their mode is then recorded by the researcher. Going through this process in a careful manner generally requires 30 minutes of researcher time per participant per day. In a 2011 Computers in Human Behaviour journal article we proposed a technique to automatically identify the activity type of events, through Support Vector Machine learning of SURF visual words (codebook of 4000 words) extracted from all the SenseCam images. After images are segmented into episodes of travel behaviour, we applied this state-of-art visual lifelogging technique to simulate how accurately automated techniques can replicate public health domain experts.

We recruited 20 adolescents from four secondary schools in England to wear the SenseCam for 5 days to record their travel behaviour. In total they gathered 135 journeys consisting of approximately 12,000 images (Kelly 2012 in American Journal of Preventive Medicine). In addition 20 adults were recruited to wear the SenseCam for 1 day to record their travel behaviour, and 99
journeys consisting of 35,900 images were recorded (Kelly 2011, International Journal of Behavioural Nutrition and Physical Activity). The data was broken into training (60%) and test (40%) sets. The test set contained 2657 images of walking, 2463 in buses, and 429 as car passenger for the adolescents. While for the adults there were 5845 test set images of walking, 765 in buses, 2738 as driving, and 2942 cycling. Table XX illustrates that event segmentation led to better automated recognition of various travel behaviour types.

*** Table 1 about here – overview of automated algorithms to identify travel behaviour ***

While an excellent criterion measure with manual input, the automated F1 accuracy scores on wearable camera images are well below 1.0. Improved image features and computational algorithms are needed to support health and travel researchers. We believe there is merit in a 2-step process as outlined in Figure 1 to segment the data into episodes, and thereafter to identify the episodes of travel. In addition, combining the visual source of data with other sensors such as GPS or accelerometers may yield better results. For example recognition accuracy on the group of adults for walking activities would be increased with the addition of accelerometer based features from .314 to .777.

*** Figure 1 about here – our proposed model of event segmentation and image recognition to process wearable image data with respect to travel behaviours ***

A future of wearable cameras in smart transportation

Wearable cameras can provide public health and transport researchers a better insight into individual travel behaviour. This may facilitate the design of better interventions to provide appropriate opportunities to members of the public to engage in more active forms of journey behaviours. While the data is very rich, it does present challenges in terms of handling the volume of data that would be generated in large scale national studies. We would welcome the input of computer scientists to facilitate the development of new episodes identification models, followed by labelling of each episode according to the journey type/category that it belongs to. Figure 1 outlines a high level overview of our proposed model to process such data.

However even allowing for these data processing challenges, we have semi-automatically analysed 350+ participant days of travel and believe that wearable cameras are ready to be used in larger studies to better understand participant travel behaviour.
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Charlie Foster leads programmes of research on physical activity and obesity in the British Heart Foundation Health Promotion Research Group in the University of Oxford, U.K. The aim of both programmes is to improve the quality of the evidence base for basic epidemiology, measurement, correlates, interventions and policy. He holds honorary academic posts at the Institutes of Human Sciences at the University of Oxford and University of Durham. He is also an Associate Researcher at the University of Newcastle, Australia and an Adjunct Professor at the Centre for Research and Action in Public Health, University of Canberra.
Figure 1 – Our proposed model of identifying travel behaviours from wearable image data. Firstly data is segmented into different events or episodes, and thereafter classified into behaviour type.
Table 1 – F1-Measure accuracy of automated image recognition algorithms, based on SURF visual words, to identify episodes of travel behaviour.

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