Passively Recognising Human Activities through Lifelogging

Abstract

Lifelogging is the process of automatically recording aspects of one's life in digital form. This includes visual lifelogging using wearable cameras such as the SenseCam and in recent years many interesting applications for this have emerged and are being actively researched. One of the most interesting of these, and possibly the most far-reaching, is using visual lifelogs as a memory prosthesis but there are also applications in job-specific activity recording, general lifestyle analysis and market analysis.

In this work we describe a technique which allowed us to develop automatic classifiers for visual lifelogs to infer different lifestyle traits or characteristics. Their accuracy was validated on a set of 95k manually annotated images and through one-on-one interviews with those who gathered the images. These automatic classifiers were then applied to a collection of over 3 million lifelog images collected by 33 individuals sporadically over a period of 3.5 years. From this collection we present a number of anecdotal observations to demonstrate the future potential of lifelogging to capture human behaviour. These anecdotes include: the eating habits of office workers; to the amount of time researchers spend outdoors through the year; to the observation that retired people in our study appear to spend quite a bit of time indoors eating with friends. We believe this work demonstrates the potential of lifelogging techniques to assist behavioural scientists in future.

Keywords: Lifelogging, SenseCam, algorithms, psychology, sociology

1. INTRODUCTION AND MAIN QUESTIONS

An embedded activity within our society is recording aspects of our lives and one of the most frequent examples of this is proactively taking pictures on special occasions like birthdays and weddings. This is a form of explicit but selective lifelogging. The field of lifelogging has been in existence since the 1980's, with early pioneers such as Steve Mann and Kiyoharu Aizawa concentrating on making smaller and smaller devices with increasing battery capacity. However these devices were single prototypes and it has not been until the release of the SenseCam that researchers outside the hardware devices arena have been able to explore the software applications of lifelogging. It is likely that digital lifelogging on a less selective but more ubiquitous basis, is set to become a more commonplace activity [1, 2].

Large-scale lifelogs however, do come with a high management cost. New techniques to automatically segment large streams of lifelog data into meaningful events have been explored [2], where an event constitutes an activity such as *having lunch, talking to a neighbour or watching television*, etc.

While there have been many developments in lifelogging technologies, with some exceptions [3, 4, 5] less work has been done on deriving actual meaningful information from lifelogs, knowing *"the what"* of given activities, and understanding how this can be re-applied in everyday life to inform our overall wellbeing. Such insights should allow us to derive new tools for lifelogs that not only support remembering [6, 7], but also advise us on future behaviours through analysis of the past. The research space here is complex and there are different lifestyle features that could be extracted from lifelogs, as well as different ways that we might interpret and map this logged data onto actual behaviours. There might even be different implications for how and what we consider to be a lifestyle feature.

In the exploratory study reported here we set out to develop an algorithm for deriving lifestyle patterns from a visual lifelog and to conduct a subjective investigation into how these automatically generated lifestyle interpretations map back onto the actual lifestyle of a group of 33 participants.

The specific research questions we address are:

1. How can we automatically determine personal, individual traits which characterise a lifestyle, from vast streams of lifelog data ?
2. What specific traits can we determine and can they be compared and contrasted across users or across time ?
3. How do people perceive their own traits and how do these perceptions compare to the actual traits automatically inferred from lifelogs ?

2. RELATED WORK

The technologies to capture a visual narrative of one's life have so far been the primary focus of lifelogging research [8]. Privacy issues around such surveillance or sousveillance (capturing data about oneself for use by oneself) [9] have also been explored by the experts in these fields [10, 7]. Although increased storage capabilities and advances in sensor technologies ha lerated lifelogging practices, the real motivations and benefits of lifelogging are still unclear. In particular, there is little evidence of whether lifelogs of our past can usefully inform our future wellbeing.

Steve Mann, now a researcher at the University of Toronto, spent much time, from the 1970's onwards, trying to capture much of what he saw through the design of head-mounted video cameras [11]. Much research in the past has concentrated on miniaturising visual lifelogging capture devices so as to encourage more users to become comfortable with this concept. Several research groups have had visual lifelogging devices that required users to wear a laptop carried on a bag around their backs [12, 13] and in some cases a head mounted camera [14]. Given the prevalence of mobile/cell phones, the WayMarkr project of New York University uses a mobile phone affixed to a strap so as to take pictures automatically [15]. The DietSense project in UCLA also makes use of a mobile/cell phone, hung via a lanyard around the neck in a SenseCam like fashion, to capture pictures automatically [16]. However capturing a visual lifelog on cell phones is still not feasible due to considerable battery limitations. Microsoft Research in Cambridge, U.K., has further advanced the field through the introduction of the SenseCam [17]. The SenseCam is small and light and from experience of wearing the device, after a short period of time, it becomes virtually unnoticed to the wearer. It holds advantages over video recorders as the device only takes images on average 3 times per minute, thus allowing a person to quickly review all the images to gist what has happened in a given day, rather than the requirement of watching a video clip in real time. An even bigger advantage is the fact that storage requirements are reduced, and also privacy concerns are not as grave as the camera takes snapshots as opposed to continuous footage. The SenseCam is now used by not only lifelogging research groups, but also by research groups in other fields as it presently offers the most usable lifelogging solution.

Recently, the focus of lifelogging research has shifted towards eliciting meaning from lifelogs e.g. specific behavioural patterns or lifestyles and investigating how this new information could influence our wellbeing. This has been partially investigated by Lindley *et. al.* [5] in their study of SenseCam use for a week's duration in the family home. The study showed that after participants looked at their sedentary images, they were prompted to change their lifestyle by, for example, cycling instead of driving, taking up exercise, and spending more time interacting with their children.

It is difficult to assess the effect that lifelogging devices have on lifestyle choices. To date, the majority of research has focused on short-term use, from a few hours use to a week [18, 6, 5]. However there are now several subjects who have been wearing a SenseCam constantly for months or even years, and one of our authors has been wearing it for over four years. It is likely that if lifelogging devices are to have any significant influence over lifestyle, it will happen during prolonged periods of use.

Segmenting lifelog data into meaningful events [2] to help make sense of large streams of visual information has also been adopted as one of the main approaches in memory archiving [19]. However, little effort has been made to understand lifelogs any further, in particular investigating what personal lifestyle traits could be embedded in one's long-term lifelog. This raises the question of whether these types of features can be automatically identified and extracted and what this could tell us about our individual lifestyle traits.

One method recently identified as a potential solution in recognising lifestyle traits from lifelog data is that of semantic concept detection [20], an often-employed approach in video indexing [21], which aims to describe visual content with confidence values indicating the presence or absence of object or scene categories. Although it is hard to bridge the "semantic gap" between low-level features that one can extract from visual data and the high-level conceptual interpretation a user gives to this data, the video analysis field has made substantial progress by moving from specific single concept detection methods to generic approaches and by combining individual concepts into groups or hierarchies, forming ontologies. The goal of the work reported in this paper is in extending preliminary exploration into concept detection in the lifelogging domain which has been evaluated on just 5 users [20]. In the work here we propose an alternative technique for concept detection, then evaluate it on lifelog data from 33 subjects and then we show the kind of lifestyle inferences that can be made from this platform for interpreting lifestyle traits and characteristics.

3. METHOD

We begin by describing the data collection tool and post-processing software analysis automatic Trait Interpreter we developed for the study. Then we describe details of the study, followed by the survey and interviews carried out.

3.1. Lifelog collection tool

The SenseCam is a small wearable device which incorporates a digital camera and multiple sensors including a 3-axis accelerometer to detect motion, a thermometer to detect ambient temperature, a passive infra red sensor to detect the presence of a person in front of the wearer, and a light sensor [17]. It is worn via a lanyard suspended around the neck. To ease privacy concerns it is worthwhile to note that audio is not recorded. Unlike a conventional digital camera, SenseCam can facilitate passive image capture, generating up to 5,000 images per day for an active user. This type of extensive visual lifelog can capture small details from our everyday activities that are often considered to be crucial in building memories of the past [22, 23, 6, 7, 24]. Figure 1 illustrates examples of everyday activities captured by SenseCam.

3.2. Trait Interpreter Tool

Preliminary explorations of lifestyle recognition from lifelogs were based on concept detection techniques derived from those used successfully in automatic video indexing [25]. A characteristic of these techniques is that they are designed to extract low-level features from relevant image/video data and to carry out the classification of those features into relevant semantic concept categories. For publicly available image and video collections this approach is highly appropriate. However as is well documented in the lifelog community, users are naturally uneasy about sharing their personal image collections with others [10].

To address this we constructed a new model of classifying lifelog data for human behaviour understanding, based on using a software application to extract low-level features from a lifelog collection which runs on a user's own personal computer. The user then sends only the low-level feature data, which are some basic MPEG-7 [26] low-level features, to the cloud for analysis. Using these features it is impossible to reconstruct what the original images look like, thus reassuring participants that content remains private and secure. We now describe how this approach is realised and evaluate its performance compared to the existing system which required all images to be sent to a central location.

3.2.1. Feature Extraction

Participants in our study used an open-source event-based lifelog browser [2] with images stored in a relational database on their local machine. A software application was sent to users which extracted two MPEG-7 features, namely ColorLayout and ScalableColor [26] from the images in their collections that they were comfortable in providing for analysis. Features were extracted from only the middle 35 images in each lifelog event, which have been shown to be sufficiently representative (i.e. 90%) of the event as a whole [3]. This meant that only approximately 35% of the users' collections were required for processing.

3.2.2. Lifestyle Trait Selection

There is a very large range of lifestyle traits that could be selected for analysis, and we used the 27 lifestyle traits outlined in Figure 1, which were previously used in the lifelogging field [20]. Indeed after further analysis of the rate of occurrence of these traits across a group of 5 users, we decided to omit 5 of them (*presentation, holdingPhone, reading, stairs, steeringWheel*). The reason for this is that these concepts occurred across very few of the participants, which meant that the example images were too skewed to too small a subset of participants resulting in a lack of sufficient heterogeneous training examples. For example only one user in our initial set of 5 users was involved in driving activity, therefore we had an insufficient distribution of *steeringWheel* traits across our participant, meaning that cross-fold validation in these instances is somewhat biased.

However more broadly it should be stressed that these 22 traits have been selected by computer scientists for the purposes of an exploratory study to investigate if our method has potential as a tool for behavioural scientists. The learning process for any newly selected traits is the same as for the 22 we use in this exploration. For example our method can be applied when more appropriate activities are selected for investigation in future, using the input of the behavioural sciences and epidemiology communities e.g. using techniques such as the Daily Reconstruction Method [27], ASAQ (Adolescent Sedentary Activity Questionnaire) [28], Canadian Occupation Therapists list [29], etc.

3.2.3. Lifestyle Trait Classification

In order to train our concept detectors, we used manually annotated images from five users. MPEG-7 features (ColorStructure and Scalable-Color [26]) were extracted as image descriptors. We used the SVMlight

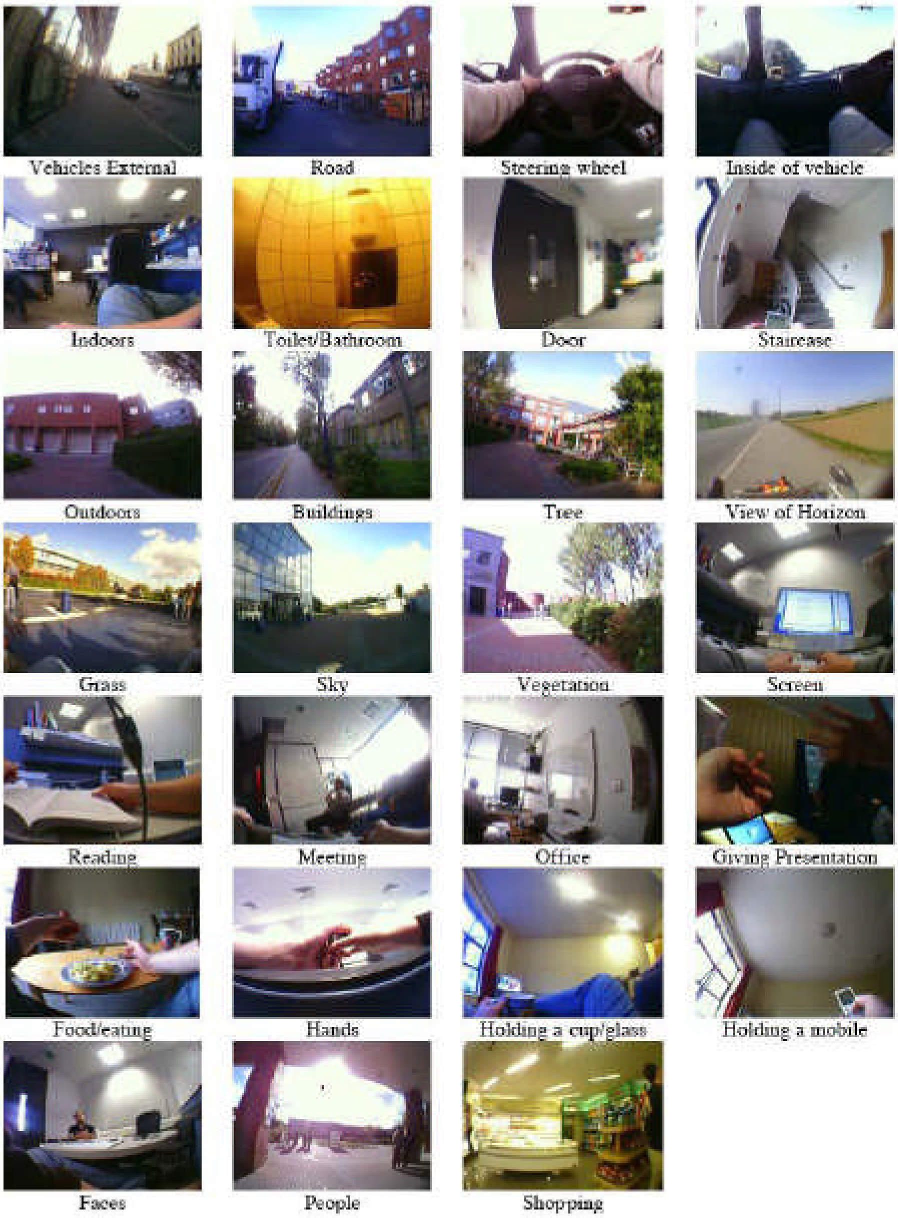

Figure 1: Example SenseCam images which represent the lifestyle activities that our trait interpreter tool automatically recognises.

implementation of the Support Vector Machine [30] and optimised the parameters using cross-fold validation. For speed of training, we split the users into just two folds. We used the RBF kernel with probabilistic output, and optimized parameters C and γ (gamma).

3.2.4. Evaluation of Proposed Technique

Building upon preliminary studies in the lifelogging domain related to this work [20], a training and test set of 87,850 images from 5 participants was used for evaluation. 9 annotators carried out a total of 152,538 judgments across the range of aforementioned lifestyle traits. Figure 2 summarises the accuracy of our technique across the 22 lifestyle traits, achieving an average F1-Measure of 65%. Encouragingly the performance of our lightweight classifier is comparable to that of the heavyweight video-analysis inspired lifestyle classification tools (avg. F1-Measure of 68%) applied in preliminary investigations in this domain. It should also be noted that the performance of both approaches far exceeds that of random (avg. F1-Measure of 15%). We believe that the level of accuracy achieved by our technique in this medium-scale sized dataset is sufficiently mature to then be applied to a large-scale unannotated set of data.

4. EXPERIMENTAL SETUP

4.1. Participants

A group of thirty three participants (9 female and 24 male, aged 22 - 60) who wore the SenseCam at some stage over the previous 3.5 years agreed to share image feature data derived automatically from the lifelog images, but not the actual images themselves, and four of these participants took part (2 female and 2 male, aged 26 - 38) in a follow-up interview. Participants were volunteers from a wide variety of backgrounds: researchers, management and administrative staff, as well as other professionals. From this, and the lifelogging practices, we constructed 4 approximage groupings of participants: *Office Workers* (6x), *Researchers* (15x), *Retired* (4x) and *Regular lifeloggers* (8x). All participants wore SenseCam for short (min 1 day) or prolonged periods of time (max 3.5 years), with a median wear period of 8 days as shown in Table 1. Regular lifeloggers wore SenseCam on a re-occurring basis and primarily came from a research background. Other groups wore SenseCam on a once-off basis.

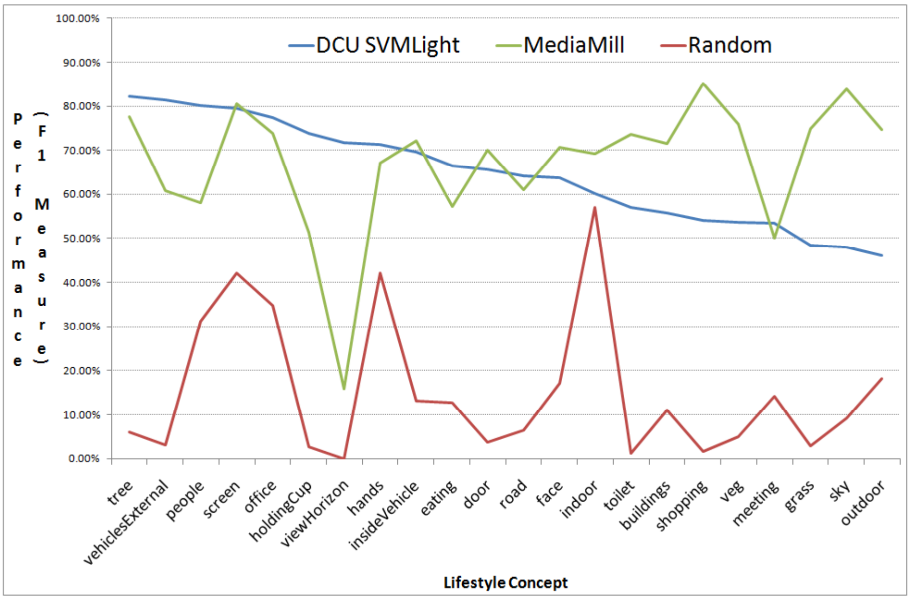

Figure 2: Lifestyle concept identification accuracy of our lightweight system (a) compared with state of the art (68%) and random (15%) classification tools.

To investigate if cross-group comparisons could be made, these groups were selected by computer scientists. Naturally there are many cross-group intricacies missed out, such as the fact that certain groups were more inclined to wear the camera at different times. For example, the *Retired* group who wore the SenseCam for an average of four days relayed a preference for recording events outside of the home, whereas long-term SenseCam wearers such as the regular *Lifelogger* group of individuals appeared more inclined to record everything, from morning until night. These examples highlight the inevitable variation of image quantity and recorded activities between the participant groups we attempted to define, and provides opportunity for future improvement.

4.2. Procedure

As this was an exploratory study, the participants were not given set guidelines as to where or how long they should wear the SenseCam. The participants were given instructions by the researchers on how to use the SenseCam. They were also given a single sheet as a reminder of its operation, which is displayed in Figure 3. In addition they were provided software to

Group (num people)	**Median Days data**	**Median Events/Day**	**Median Images/Day**	**Avg Daily Duration**
Office Workers (6)	7	19.5	1599	6h 55m
Researchers (15)	8	20	1640	7h 15m
Retired (4)	3.5	25.5	2091	10h 30m
Lifeloggers (8)	42	18.5	1517	10h 21m
Overall Averages	15.1	20.9	1712	8h 45m

Table 1: Information on data gathered by our participants, broken into general social groups

browse through their images [31]. Ethical approval was obtained from the Dublin City University Research Ethics Committee, the group charged with responsibility for monitoring and approving research projects from an ethical and privacy standpoint.

The study then consisted of two stages: 1) automated *lifestyle trait interpretation* and 2) subjective *lifestyle trait feedback*, each of which are described in detail below.

4.2.1. Lifestyle Analysis Phase

In the *lifestyle trait interpretation* phase, we collected lifelog data from 33 participants. A total of 3,532,904 lifelog images were gathered which were then segmented into 43,072 events using an open-source event-based lifelog browser [31]. Participants then used a feature extraction software application which processed the lifelogs, and returned the low-level image output of a total of 1,314,376 images.

The MPEG-7 ColorLayout and ScalableColor features were extracted at a speed of approximately 10 images per second across the participants' machines. Thereafter the MPEG-7 features were input into our lifestyle trait interpreter tool to be classified into the relevant traits. This phase was completed at a speed of approximately 20 images per second on a single CPU. The trait classification outputs with an average confidence score of greater than zero over all (middle 35) representative images in each event were classified as positive examples of a given trait.

4.2.2. Lifestyle Feedback Phase

After identifying personal traits, 4 participants who donated features from their lifelogs were interviewed. We conducted one-on-one interviews where

Using SenseCam

Turning on/off – you can turn the SenseCam on or off by pressing the button in the top of the device for a few seconds. When it is turning on it will make a beep sound at an orange light will appear beside the button.

Turn the SenseCam off when you are not wearing it to save the battery. You will most likely only need to turn it off when you are going to bed or if you decide you do not want it to record anything for an extended period.

Privacy button – press this button to temporarily stop the device from taking pictures. It will reactivate automatically after 7 minutes.

Activate button – this button allows you to take a picture manually or to re-activate the device if you had previously pressed the privacy button.

Status lights – an orange flashing light will indicate every time an image is captured. A red light indicates that the privacy button has been pressed and the device is not taking any images at this time.

Charging
You will be given a charger lead with a plug on one end and a small square plug on the other end. It is recommended that you charge SenseCam at night when you are sleeping so that the battery will be full for the next day.
To charge the SenseCam, put the small end of the plug into the SenseCam in the slot on its side (see picture) and plug the other end into your domestic plug socket.

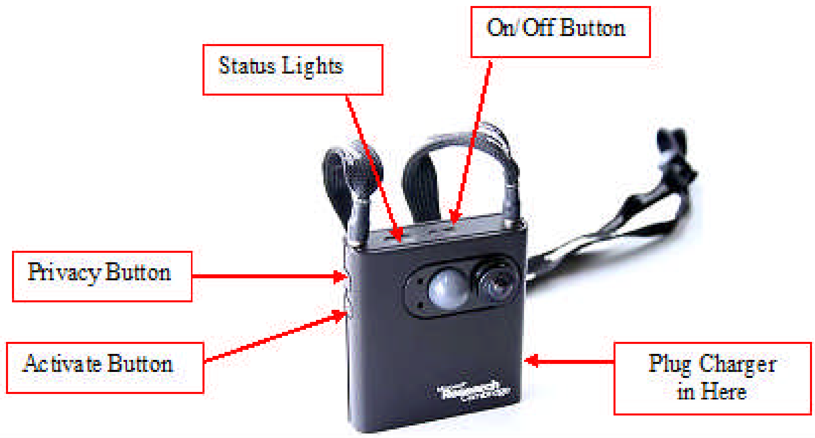

Figure 3: Information sheet given to participants as a reminder on how to operate the SenseCam.

we asked 4 participants to describe their personal behavioural traits and provide feedback on how well lifelogging devices fitted into their style of life and what they perceived their own personal lifestyle traits to be. Participants were asked about each of the following aspects:

- Highlighting personal traits — what types of personal traits could lifelogging devices help highlight;
- Perceived trait frequency — perceived frequency of selected traits, specifically how frequently participants thought they undertook a given set of activities during their ordinary week;
- Fitting in with lifestyle — to what extent could SenseCam be used as a tool for collecting individual lifestyle characteristics.

The interviews contained open-ended questions about what people perceived their dominant traits to be and how lifelog images helped them to highlight these traits. We present these as quotes through the article.

5. RESULTS

This section reports the findings of applying the trait interpreter tool on our group of participants. Obviously these findings will not tell significant insights into human behaviour as this is not a large scale randomised control trial. However these findings in our exploratory study are of interest as they demonstrate the future potential of using this automated behaviour capture tool. The following reports on findings from the *lifestyle trait analysis*.

5.1. Number of traits elicited

Across the 1,013,878 minutes of total lifelog data collected by our 33 participants, our tool determined that most time was spent indoors (mean of 7h 15m per person per day of SenseCam wear time) with the least time being spent in the restroom (mean of just 13sec per person per day of SenseCam wear, probably indicating people generally switch the camera off for these activities). Figure 4 sums-up personal traits identified by our automated Trait Interpreter across all 33 lifelogs.

Under the conditions of our study, and given the output of our trait interpreter tool, the largest part of the time, 83%, was spent *indoors*. People also spent a lot of time, 39%, socializing with other people, as inferred by co-occurrences of the (*people* 39%) and (*face* 20%) traits. Personal computer based activities (*screen* 9% & *hands* 25%) were also prevalent traits captured by our Trait Interpreter.

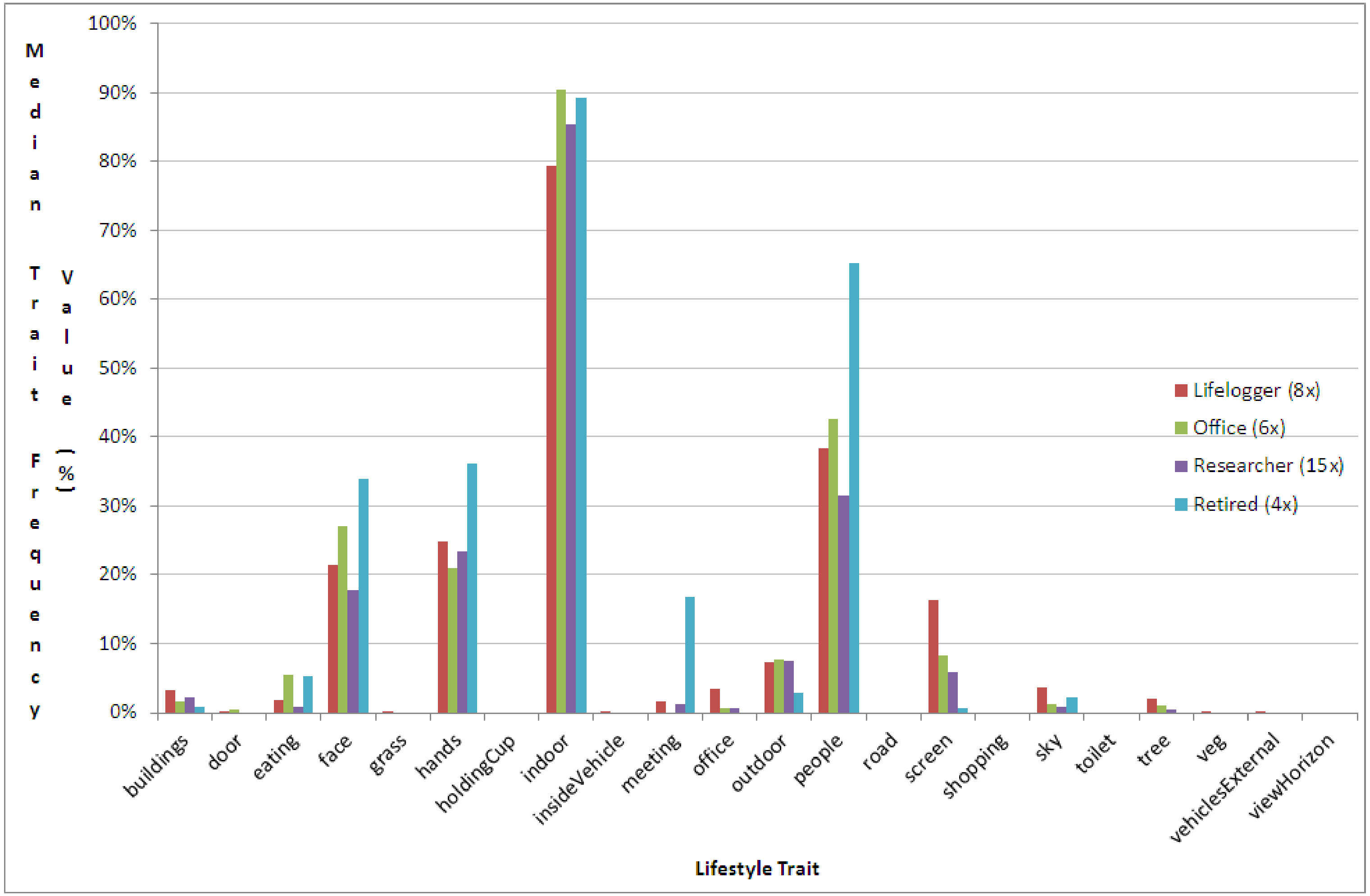

Figure 4: Time spent on each of the 22 automatically identified activities across entire set of lifelog data gathered by 33 participants

Trait 1	**Trait 2**	**W**	**Trait 1**	**Trait 2**	**W**
Face	people	0.79	hands	people	0.55
Buildings	sky	0.77	tree	veg	0.54
Sky	tree	0.74	grass	tree	0.53
Buildings	tree	0.66	hands	screen	0.53
hands	indoor	0.65	face	hands	0.5
indoor	people	0.65	indoor	screen	0.49
buildings	outdoor	0.62	outdoor	tree	0.48
grass	veg	0.58	grass	sky	0.48
outdoor	sky	0.57	office	screen	0.47
face	indoor	0.56	sky	veg	0.44

Table 2: Top 20 most strongly co-occurring lifestyle traits in our study

Before carrying out further analysis on the outputs of our lifestyle analysis, we decided to carry out a "common sense" logic approach on some of the concepts. Firstly there was a strong negative correlation between the *indoor* and *outdoor* lifestyle traits, which follows logical expected outcomes (see Figure 5). Also consider the co-occurrence of different traits outlined in Table 2, where the co-occurrence factor is $W = c_{ij}/\sqrt{(s_i s_j)}$, which normalises co-occurrence by the likelihood of individual concepts. Again quite logically we can see that when the trait *face* is present, the trait *people* is also highly likely to be present, and also with other instances such as *sky:tree, grass:veg, hands:screen*, etc.

5.2. Do traits differ among defined groups ?

As described in the participants section (Section 4.1) and in Table 1, we identified 4 participant groupings: *office workers, researchers, retired* (people from non-computing background), and *lifeloggers* (avid enthusiasts, all researchers by profession, who wear the SenseCam for long periods of time). We then compared the relative number of occurrence of traits between these different groups. As Figure 6 illustrates, the *retired* group of participants appeared to spend more time *meeting* with friends and relatives. A possible explanation for this may be that they are not as engaged with technology given they spend less time in front of a personal computer *screen*. An interesting trait related to the *lifeloggers* group is that they appear to wear the device for a wider range of activities, thus traits such as *insideVehicle* occur much more frequently when compared to other groups. The *office workers*

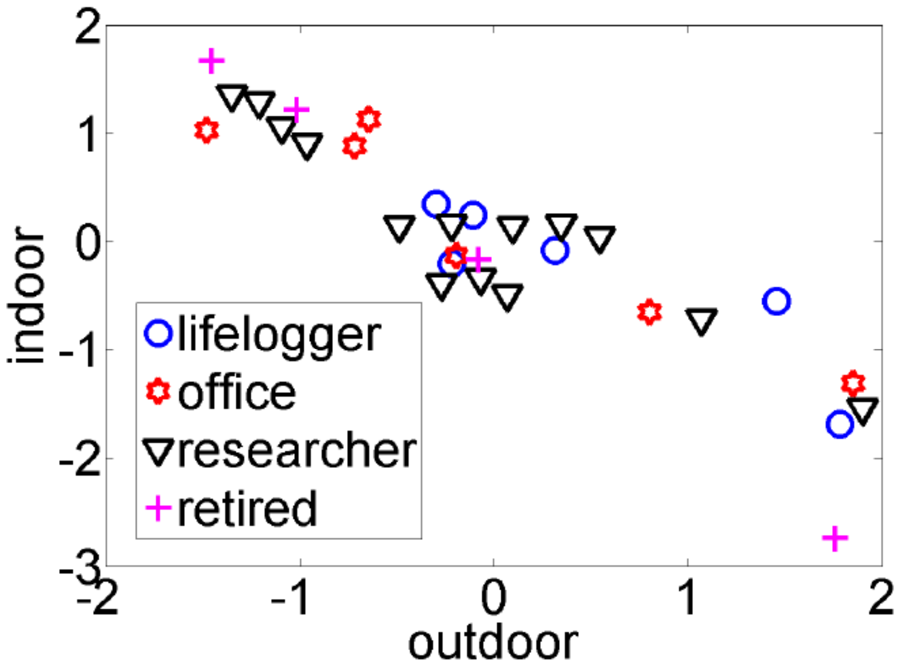

Figure 5: Correlation of time spent *outdoors* versus *indoors* by our participants, illustrating a spectrum along which a user can evaluate his/her lifestyle.

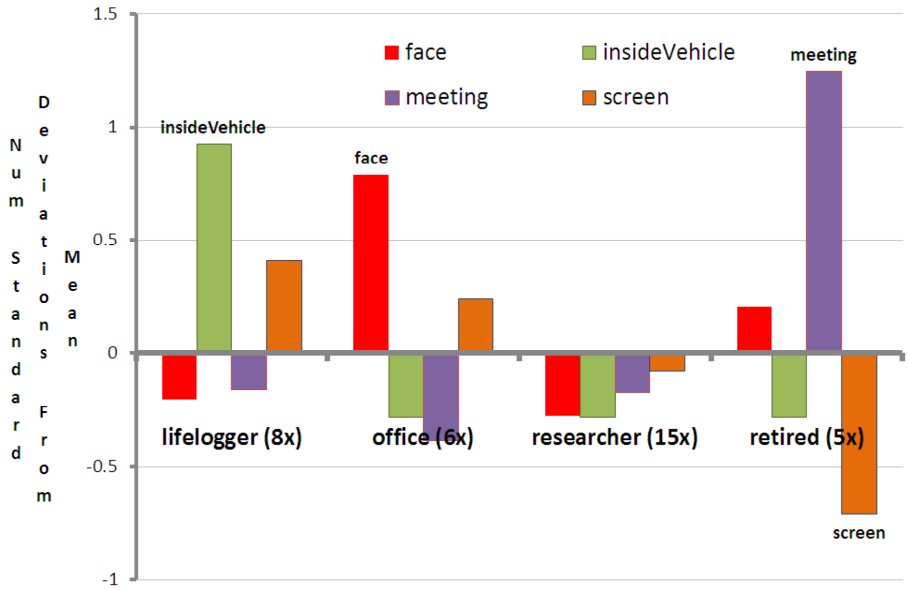

Figure 6: Time that 4 groups of participants in our study spent on 4 selected lifestyle categories. The x-axis (y=0) represents the mean rate of occurrence of lifestyle traits and the y-axis measures the number of standard deviations away from this mean.

in our study exhibited more *face*-to-face interaction than the other social groups, while the *researchers* grouping demonstrated the least proportion of social contacts among the groupings defined in our study.

5.3. Did some groups miss their lunch ?

We now demonstrate the potential of our tool in eliciting a detailed daily breakdown of engagement in a given activity, and how this may be used in future human behaviour validation studies. For the purposes of this demonstration we consider the eating patterns of the different groups of participants (results illustrated in Figure 7). We observed that *office workers* appeared to have a regular set pattern of eating between 11am and 2pm, while had an evening meal between 7pm and 8pm, before supper at 10pm. The *retired* groups of users appear to have regular lunch at 1pm, and then evening dinner between 7pm and 9pm. But the *researchers* and *lifeloggers* have less set patterns of meal times, which may suggest further implication on their work-life balance and wellbeing. Again this requires further validation in large scale field trials, but could be a powerful means of contextualising traditional methods used.

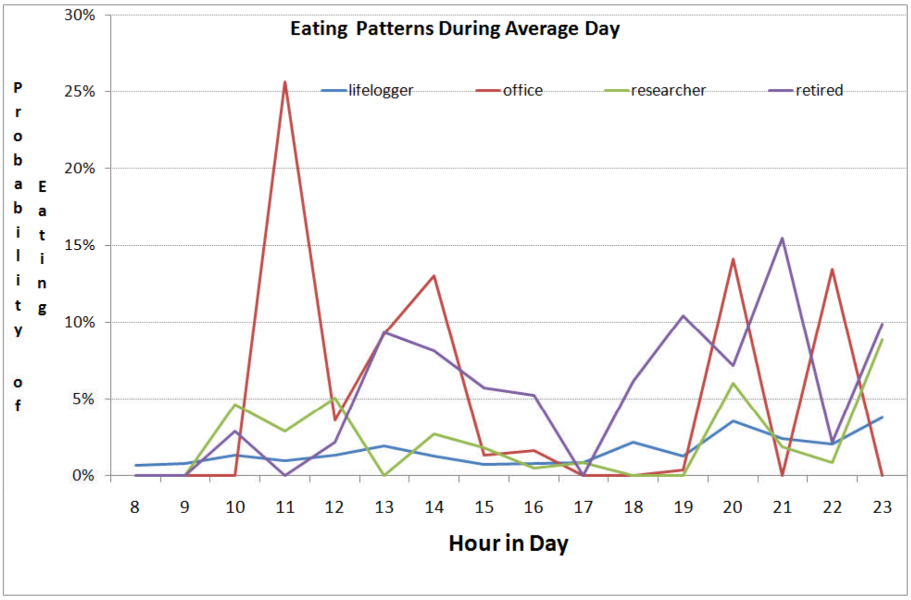

Figure 7: Participant eating patterns during a typical day as measured by our trait interpreter tool in this exploratory study.

5.4. Is there potential to compare lifestyle trait profiles ?

Since it is possible to represent each user as a vector with 22 associated lifestyle feature dimensions (with each dimension representing the fraction of time that the participant was engaged in a given activity), we can exploit these vectors to group together participants by lifestyle similarity. Figure 8 shows a plot of the first 2 PCA components[1] for each participant, as the first 2 components contained over 80% of the variance. A majority of the 33 participants appeared to cluster closely into the groups we pre-defined. A possible interpretation that would require further study is that if one is a *researcher* or a regular *lifelogger*, they tend to spend a lot of time with like-minded people and over time adapt to some group lifestyle traits. Another possible observation is that, *retired* and *office workers* tend to retain more individually pronounced traits, which may explain the individual points being positioned further away from the cluster centroid in Figure 8.

[1]First 2 PCA components were selected from a 22-element vector representing each participant, with each element representing the % time spent on a given activity

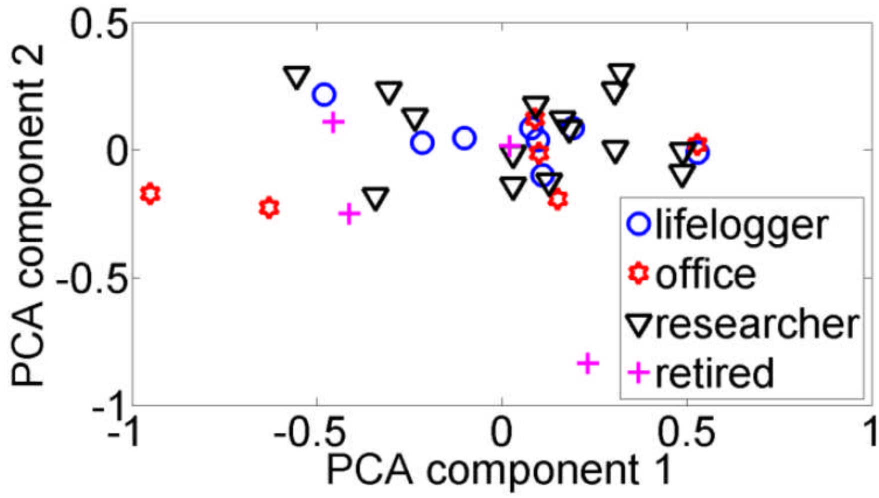

Figure 8: Clustering of participant groups in our study by lifestyle traits using PCA analysis.

5.5. *Periods where more time is spent indoors*

Within the group of *lifeloggers* we further investigated the average amount of time spent *outdoors*. The reason for selecting this grouping was that they had captured the most data over longer periods of time (median of 42 days gathered as noted in Table 1). Figure 9 suggests that more time may be spent *outdoors* in the Summer months when there is more daylight, than during the Winter months.

5.6. *Lifestyle Trait Interpreter Reliability*

To qualitatively investigate the reliability of the output generated by our Trait Interpreter tool we carried out follow-up interviews with 4 (2 female, 2 male, mean age = 30) of the participants who donated their lifelog image features. The interviews were broken down into 3 sections or phases. In the first phase, users where asked to select from a list, the 10 most frequent traits that they believed to be captured by their own lifelog images. Then, during the second phase, participants were shown a breakdown of the time they spent on these pre-defined 22 traits that our algorithm had identified and they could also contrast this information with traits from the other 32 participants. Finally, they were then asked to comment on this automated interpretation of their lifestyle.

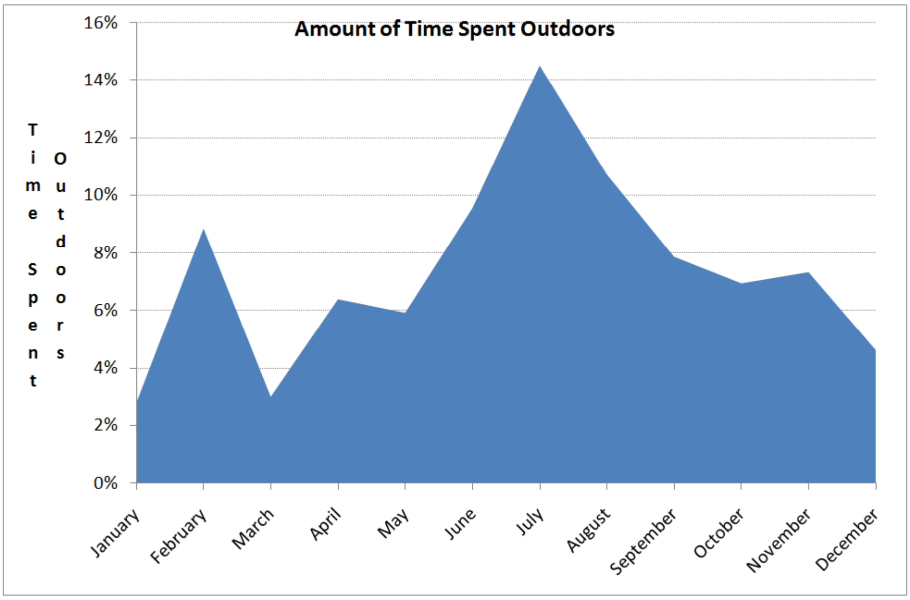

Figure 9: Time spent outdoors by the participants we placed in the *lifeloggers* group, calculated over a period of 3.5 years.

The traits that participants perceived as being the 10 most frequent traits (see Figure 10) were compared to the 10 most frequent traits identified by the Trait Interpreter tool. The accuracy between participants identifying own traits and those generated by the Trait Interpreter was encouraging (see Table 3) in our study. We now comment on some anecdotal observations.

Participant comments highlighted an overwhelming interest in being able to see automatically generated interpretations of their own personal traits that they could easily identify. After viewing the automated trait identification output, to our surprise, participant 3 said that she felt that the Trait

Participant	**Crossover between self report and our lifestyle trait tool**
1	70%
2	70%
3	50%
4	57%

T le 3: Accuracy between self-identified and automatically identified personal traits.

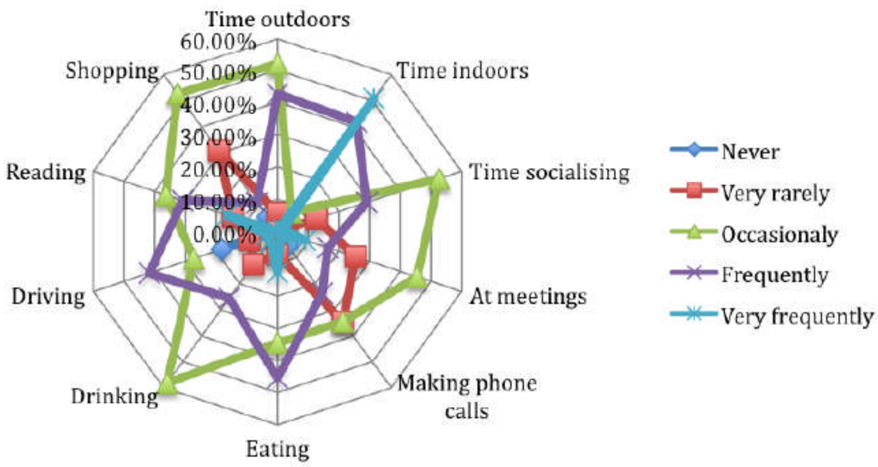

Figure 10: Perceived frequency of time spent on lifestyle activities by 4 participants in interviews.

Interpreter ranking was actually more accurate than her own ranking. They were all genuinely surprised how much time they actually spent indoors: *"I should meet more people or go out more, I am too much indoors. I can see the overall imbalance and maybe I'll try to change it"* and *"I don't see much of nature. Grass is practically not there"*. Other traits around eating habits specifically showing lack of time spent having meals, brought out some weight concerns for one of the participants: *"I should spend a bit more time eating, I'm very thin. I'm only 55 kilos"*.

The interviewed participants agreed that the presentation of such detailed automatically-generated summaries of their own lifestyle traits could spark motivation for a change in their behaviour. Further application of such visualization could lead to investigating how personal traits change over time and across seasons e.g. Summer versus Winter. Participants were also interested in being able to compare their own traits and frequencies of occurrence to those of their friends and peers.

6. FUTURE WORK

We believe that this article provides the first investigation into the elicitation of various human behaviour activities from visual lifelogs. To reach this stage, much effort has been required to find willing participants to gather data. Also, advances have been required in managing the data through detecting distinct events or activities [31]. Building upon the visual processing work of the TRECVid video community [32], we have been able to apply the automatic detection of 22 concepts to visual lifelog data. We feel that the approach we've taken in this work has been successfully "sanity-checked" through the anecdotal observations reported in this article. However there is naturally a number of future milestones that need to be achieved for lifelogging review technologies to truly be more acceptable to behavioural scientists and also the wider population. We now highlight these challenges:

- Identifying a set of base concepts to generalise across lifestyle activities - While the techniques and processes mentioned for the activities covered in this article, can be re-applied to find new activity types in future, we recognise that a more appropriate set of activities should be selected. The lifelogging community should actively seek the input of the behavioural sciences and epidemiology communities e.g. using techniques such as the Daily Reconstruction Method [27], ASAQ (Adolescent Sedentary Activity Questionnaire) [28], Canadian Occupation Therapists list [29], etc. From this a set of base concepts or classes can be identified to provide the technology with a set of activities to automatically identify.

- Evaluation across a more diverse set of users - As noted by Froehlich, Findlater, and Landay the computing community is quite weak in recruiting large populations of representative users for experiments, especially when compared to the behavioural sciences community [33]. However they also note that the computing community has a strength in offering possible solutions or interventions. This article mirrors the general trend, in that this study "sanity-checks" our generic framework, but that our selection of user groups is far from ideal. Over a period of 3.5 years, most of our recruited participants were generally from technology backgrounds (apart from a a number of retired citizens) and only wore the camera for short and varying periods of time. However as the technology becomes more accepted [8] it is now becoming more realistic to recruit a large number of diverse users to investigate how successfully technology can identify their lifestyle traits. Again interaction with the behavioural sciences community is key.

- Multi-modal concept detection - In addition to visual images, other types of lifelog information exists such as accelerometer [17], GPS [34], Bluetooth [35], etc. The fusion of these sources of information should be investigated to evaluate their use in improving the performance of automatic lifestyle activity recognition.

7. CONCLUSION

This study extends the notion of lifelogging by starting to better capture human behaviour. Previous work has viewed lifelogs as archives [19] often organised into events [2] or as a data source for triggering recall [6, 7]. Instead in this study, we evaluate a new technique for automatically eliciting personal traits from visual lifelogs. We trained classifiers which were able to identify 22 different lifestyle traits ranging from detecting whether someone was meeting friends or having lunch. We applied those chosen classifier models to 3+ million lifelog images collected by 33 participants at some point during a period of 3.5 years. More specifically, this work shows that lifelogs have the potential to inform our future wellbeing through automated analysis of past traits. A subset of questioned participants noted that automatically elicited traits appeared correct and in anecdotal cases there was tendency to trust the automatic traits more than self perceptions.

There are important design implications that follow from this work. While it is important to collect rich recordings about our past, it is also critical to consider what traits people might want to track and examine to help inform future wellbeing. We have noted that in future, close collaboration with other disciplines will be necessary to advance this work. It is also crucial to consider how to present this data. Since intention to share, motivates lifelogging, *who* to share it with and *how* is an interesting research question. Facebook and other social networking sites could support trait sharing amongst different social groups. Our results on a sample of 33 participants suggest that some social groups tend to adopt similar traits.

Critics of lifelogging [24] argue that lifelogging simply accumulates huge collections of mundane data. But our study shows that providing automated and meaningful extractions of traits can address this criticism. This work represents a milestone towards a more structured behavioural sciences style experiment, and after addressing some of the future work challenges mentioned in Section 6, we envisage a number of useful applications such as:

- Assessing one's own health and wellbeing e.g. how active we are, what foods we have been eating ?

- Automatically creating labelled personal diaries of past activities and interests;
- Improving personal efficiency through understanding how much time was spent on specific tasks without having to actively log anything e.g. [36];
- Helping to determine the traits, correlates, and interventions that influence population health e.g. [37];
- Providing quantitative lifestyle improvement metrics as a consideration factor in determining the success of treatments in clinical trials.

These are just some of the possibilities that have now opened up following this exploration study into new automated lifestyle trait detection technique. Our hope is that future work will continue to systematically examine the ways in which lifelog data helps understand personal traits and inform future personal wellbeing. There are still challenges in further miniaturising lifelog capture devices, and also many retrieval challenges associated with lifelogging. However in essence we believe that this novel platform of automated lifestyle trait analysis represents the wider emergence of lifelogging to support researchers in passively measuring human activities.

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