Using Periodicity Intensity to Detect Long Term Behaviour Change

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Abstract
This paper introduces a new way to analyse and visualize quantified-self or lifelog data captured from any lifelogging device over an extended period of time. The mechanism works on the raw, unstructured lifelog data by detecting periodicities, those repeating patters that occur within our lifestyles at different frequencies including daily, weekly, seasonal, etc. Focusing on the 24 hour cycle, we calculate the strength of the 24-hour periodicity at 24-hour intervals over an extended period of a lifelog. Changes in this strength of the 24-hour cycle can illustrate changes or shifts in underlying human behavior. We have performed this analysis on several lifelog datasets of durations from several weeks to almost a decade, from recordings of training distances to sleep data. In this paper we use 24 hour accelerometer data to illustrate the technique, showing how changes in human behavior can be identified.

Author Keywords
Lifelogging; periodicity; detecting behaviour change; periodogram intensities;

ACM Classification Keywords
H.5.1 [Multimedia Information Systems]: Miscellaneous; H.4 [Information Systems Applications]: Miscellaneous.

Introduction

There are now many types of sensors available for *quantifying the self*, both wearable devices to measure physiology, capture activities and log interactions with others, as well as sensors built into our environment like CCTV, wireless device loggers and online log files to capture our virtual activities [4]. No matter what the purpose for quantifying the self, also referred to as lifelogging, it is accepted that there is a need to analyse and structure the raw data into higher semantic units, popularly in the form of "events", in order to make the lifelog usable [1]. This reflects a fairly widespread approach taken to managing large volumes of unstructured data streams like digital video, for example, where video is segmented into shots, scenes and then programmes.

For lifelogs, automatic analysis and structuring into events is a natural first step and is usually based on measuring local similarities within a region or sliding window of time, and in this way detecting large changes, either sudden or gradual, in the underlying stream of lifelog data. This could be similarity between images from wearable cameras or measurable shift changes in streams of accelerometer of physiology data 1. Such automatic segmentation of lifelog facilities subsequent use of the lifelog for applications like searching or browsing, or re-locating a single past event but it is not good at giving an holistic overview of the lifelog. For applications like measuring behaviour change we need to have a very high level overview of the lifelog because it is only then that such behavior changes can become apparent.

In previous work, researchers including ourselves have tried to use lifelogs in order to recognize and characterize human behaviour [7, 2, 7] but only after the raw data from the lifelog had been processed into semantic units like events or scenes. The problem with this approach is that much of the repeating signals which constitute a fundamental part of human behaviour, are lost in the aggregation from raw data to higher level events and thus some of the regular patterns, and deviations from those patterns, which make up our regular human behaviour, cannot be re-constituted from the processed lifelogs. We have identified an opportunity to identify behavior change that does not require converting low-level signals into higher-level events and there are benefits to this.

In the work reported here we take a step back and we detect human behaviour, and changes in behaviour, directly from raw and unprocessed lifelog data. This treats the problem as a signal processing challenge and because we are agnostic as to the type of lifelog data, we can use the same approach to process a lifelog, independent of the kind of lifelog sensors or the sampling rate used.

Human Behaviour and Periodograms

Much of human behavior is built around regular repeating cycles in our lives. The best example of this is the circadian rhythm, the daily cycle of sleep, wake up, rise from bed, self-groom, eat, work or play, eat, entertainment and then back to sleep again, with occurrences of things like socializing, self-improvement and exercise sprinkled throughout the day. Much of our physiology, our resting heart rates, mood, food and drink intake, digestion, alertness and fatigue and other bodily functions move through regular cycles on a schedule that is both predictable and yet has

Figure 1. GENEactiv accelerometer, worn on the wrist

counterpoints. These regular cycles and interruptions change as the changing nature of our days demand.

There's a series of studies that in addition to being a health-promoting activity in itself, shows that exercise improves the rhythm of our lives [6, 3]. In this work, scientists asked young adults and older people to wear activity monitors for a week as they went about their normal lives and then plotted each volunteer's 24-hour movements, finding that younger people move quite a bit during the day. The study also found that there are patterns of movement levels which are more consistent the more exercise the wearer takes.

This result is interesting in that it re-enforces what we already know, namely that we have regular cycles of activity. However the regularity and the strength of our cycles is important and we may want to measure the levels of that consistency or regularity because shifts in the strengths of this could be correlates for shifts in our behavior.

A periodogram is a visualization of the power spectral densities for a continuous spectrum of frequencies calculated from a stream of data values. Periodograms have been used in application domains as diverse as astronomy to radar to determine which are the repeating cycles with the dominant frequencies in a datastream. When periodograms are applied to lifelogs they can reveal daily, weekly, seasonal, perhaps monthly or even annual cycles which form a natural part of human behavior. Periodograms work best when the data is regularly sampled and is continuous, i.e. has no missing values, though past work has shown that the Lomb-Scargle periodogram which handles missing data values, can be successfully applied to generating periodograms from non-continuous lifelog data [5].

Data sets

We have used several different lifelog datasets to explore periodicity in human behavior, as reported elsewhere in 5. These include sleep data from an individual recorded over 2.5 years, sports training data from an individual over a 10-year period, running data over a 2-year period and sleep data from a small cohort of people with early stage dementia including measuring sleep. For each of these we have identified periodicities with strong frequencies at daily, weekly, seasonal or annual cycles depending on the length of the dataset.
To illustrate how periodicities can indicate changes in human behavior, for the specific contribution of this paper we focus on yet another dataset, captured using a GENEactiv accelerometer (ActivInsights, Kimbolton, UK) worn on the wrist and sampled at 40Hz, shown in Figure 1. For this experiment, 26 adults took part and gathered data continuously, 24 hours per day, for between 28 and 72 consecutive days. Each of our participants took part in this study because they have some sleep issues and during the lifelogging period there were some sleep improvement interventions introduced. We will be interested to see if the effects of the interventions on behavior can be detected in the periodicity analysis.

The raw data from the accelerometer was summarized to 60 second epochs using the gravity-subtracted sum of vector magnitudes and a sample of this for subject 102 from the experiment is shown in Figure 1. Because of space limitations we illustrate our work on just one participant. This plot of the overall activity levels illustrates several isolated periods of high activity, probably exercise of some form, throughout the 12-week period of data logging but there is no evidence of changes in behavior.

For each of the 26 participants we generated a periodogram, and a sample for the same participant, number 102, is shown in Figure 2. This shows a reasonably strong energy level around the 1-day point and a smaller peak at around the 12-hour point. Compared to some of our other participants who have gathered similar data, the regularity of this individual's daily cycle is not particularly strong for the whole of the 12-week period, suggesting that s/he may work shifts or just have a very disorganized and irregular lifestyle.

Periodograms and Behaviour Changes

To explore further how the regularity of an individual's lifestyle may strengthen and wane over time, we calculated the strength of the periodicity of the 24-hour cycle for time-lagged overlapping windows of 3 days duration, throughout the 12 week logging period, and plotted these, again for the same participant, in Figure 3. In effect what this shows is the strength of the subject's daily 24-hour lifestyle pattern based on their activity levels as measured from the wrist-worn accelerometer. What it shows is that during the first 3 weeks there was a lot of change in lifestyle on a day-to-day basis. Between weeks 3 and 7 there was a period of almost complete irregularity and then at week 7 the subject entered a period of very regular behavior which ceased around week 10 and then resumed before the end of the logging period. The sleep interventions which involved personalized smartphone alerts to promote smarter sleep hygiene, occurred at weeks 3 and 7, and their effects can clearly be seen in Figure 3.

Discussion

The method for detecting behavior changes shown in the example activity levels from an accelerometer worn over a 12-week period also works equally well for the other datasets mentioned earlier. This now offers a way to detect shifts in behavior from raw lifelogs but these changes need to be interpreted by processing the lifelog into higher semantic units.

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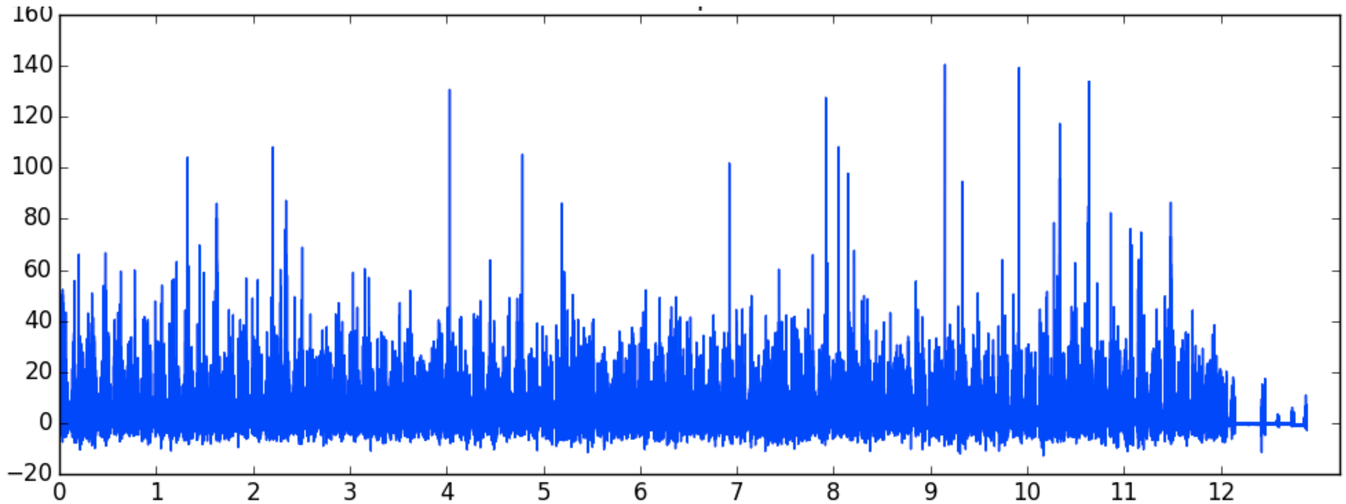

Figure 1: Activity levels for participant 102: x-axis shows weeks, y-axis shows raw activity levels in 60-sec epochs

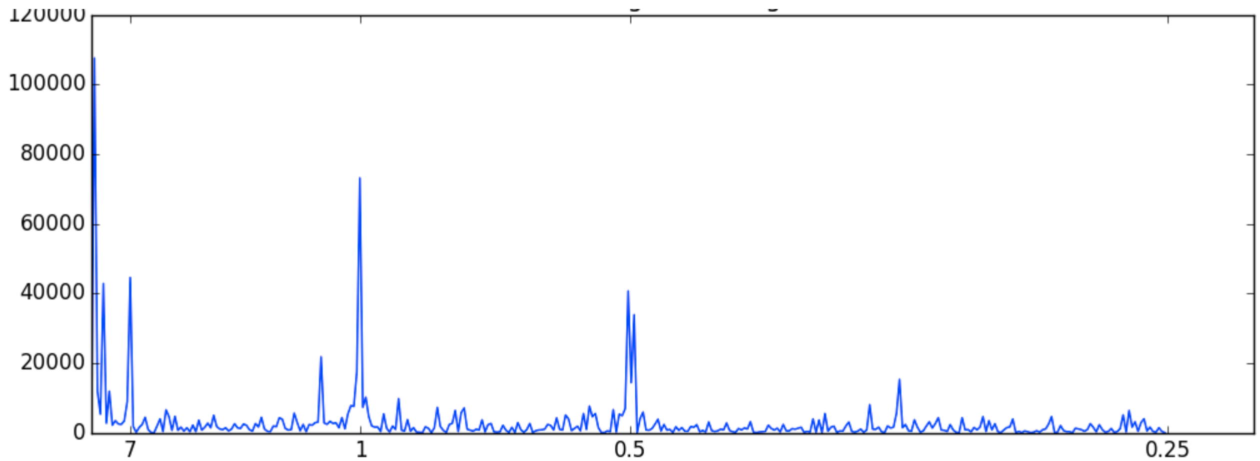

Figure 2: Periodogram for participant 102: x-axis shows frequency in days (0.25 = 6 hours) on logarithmic scale, y-axis shows intensity

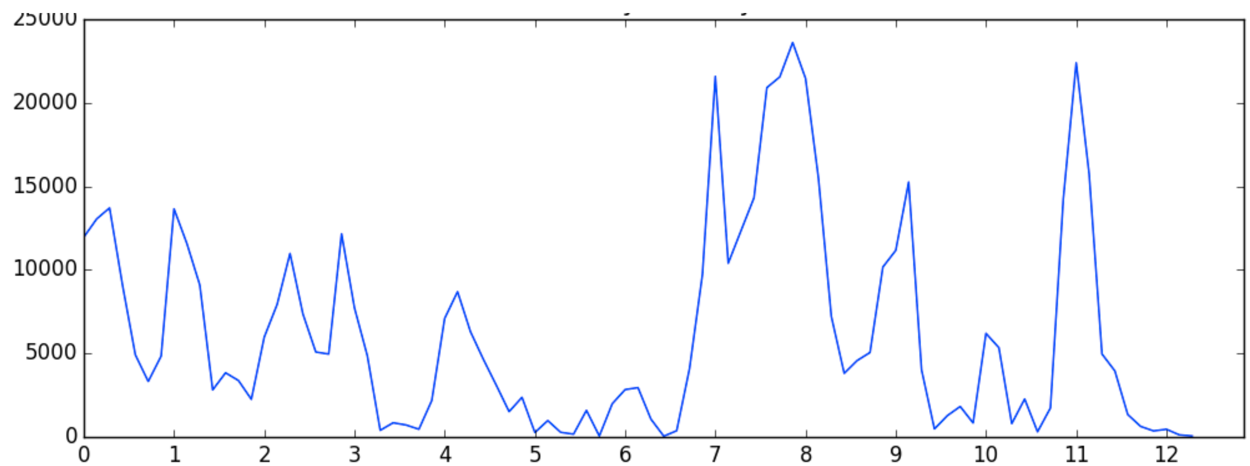

Figure 3: Intensity of periodicity for participant 102: x-axis shows weeks, y-axis shows strength of 24-h periodicity