Periodicity Intensity for Indicating Behaviour Shifts from Lifelog Data

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***Abstract*—Periodic phenomena or oscillating signals can be found frequently in nature and recent research has observed periodicity appearing in lifelog data, the automatic digital recording of everyday activities. In this paper we are exploring periodicity and intensity of periodicity in big data settings, especially when the data is noisy, unevenly sampled and incomplete. An interesting possibility is to compute the intensity or strength of detected periodicity across the time span of a lifelog to see if it reveals changes in this strength at different times, indicating shifts in underlying behaviour. In this paper we propose several metrics to estimate the intensity of periodicity, longitudinally. Evaluation of these metrics is conducted on simulated high-level activity data generated from a proposed model. We also explore periodicity intensity calculated from two real lifelog datasets using. One is "big" data consists of low-level accelerometer data and another one is high level athletic performance data.**

I. Introduction

Lifelogging is the ambient, digital capture of any of several possible data sources which log the ordinary day to day activities of a person performing typical activities of daily living [1]. Devices used for lifelogging can include accelerometers, GPS trackers, wearable cameras, or other sensors to measure aspects of our physiology like heart rate. Prefarably, personal lifelog data would be captured by a variety of sensors at synchronised frequencies covering a period of time as long as possible and involving a good number of subjects. In this case, personal lifelog data can be considered as a big data problem. To tackle personal big data, capturing, storing and organizing of such data have become popular research areas. In order to make personal big data applicable for populations, there are several possible purposes for such recording of the daily activities and lifelogging is already widely used in medical and therapeutic applications such as support for reminiscence therapy, a tool used in memory reinforcement and helping to promote healthy lifestyles [2].

For many years, research into lifelogging has focused on processing lifelogs into events. Researchers have described a visual diary of lifelog images constructed by clustering images based on low-level image features such as a colour spatiogram and block-based correlation between images [3]. The study by [4] showed a method for detecting event boundaries in which images (or blocks of images) are compared to their neighbours to determine their dissimilarity. A novelty detection algorithm [5] was developed based on identifying deviations from the wearer's normal behaviour.

In our work we are interested in using lifelogs to detect behavioural change over long periods, of the order of months. We do this by using a periodogram to detect the strength of all periodicities (frequencies) from a lifelog and then taking the strongest periodicity, calculate how strong that is across the lifelog, or in other words, how regular the subject's behaviour patterns are and how they change over time. The premise here is that changes in the regularity of a lifestyle are indicators of changes in our underlying behaviour, and detecting these may highlight times in our past when this has happened as a result of a health issue, stress, relationship problems or the result of some external intervention. Becasue of the nature of personal big data, we are expecting any methods that we propose could be potentially applicable to such data. That is the reason we choose to conduct an experiment on such real life personal big data scenario.

In the next section of this paper we provide some background to previous work on periodicity detection from lifelogs and then we describe our methodology and a range of possible metrics for calculating periodicity strength. Following that we introduce a model for generating synthetic lifelog data to which we apply the metrics we propose, and then we introduce, and run experiments on, two lifelog datasets each of which reveals changes in periodicity strength which are indicative of changes in underlying behaviour.

II. Background

In previous work [6], we have shown that there is periodicity in longitudinal lifelog data, and that this can be detected using a basic periodogram. By using methods such as DFT/FFT we can compute periodograms for any complete data series and we are able to detect periodicity in that data with satisfying performance. As for unevenly sampled data, parametric methods such as LG-periodograms could be used to estimate the spectrum of such data series and compensate for the missing data. In this paper we focus on how to define and calculate the degree to which a frequency is periodic in lifelog. For this reason we introduce the idea of *intensity of periodicity* where the output is a value indicating the regularity of a certain periodic frequency within a given time span of a lifelog. If we use a window, incrementally sliding through a whole dataset or lifelog, the output would be a series of values indicating the change of regularity for that period, within the whole lifelog. Changes in intensity of periodicity at a given frequency reveal changes in data which could correspond to changes of underlying behaviour and this provides a practical perspective for researchers to review lifelog data.

Here are the high-level steps we follow to calculate period intensity changes with time:

1) Choose a suitable length window, within which a periodogram can be calculated.
2) From the periodogram, identify the frequency that is exactly and/or close to detected significant periods of the lifelog, and calculate the corresponding energy. Depending on the size of the window, the most significant period within a window may differ from the most significant period detected using all data.
3) Move windows and repeat the second step, until there are no more data points available. The series of energy values generated will correspond to the regularity of the selected frequency.

III. Methodology

In order to define what period intensity is, we try to understand what factors may relate to modelling lifelog data, as those factors may result in changes in lifelog data. We then focus on using those factors to generate simulated data with known intensity. With the simulated data can we then compare the performance of different metrics to measure the intensity of periodicity quantitatively, against ground truth.

A. Activity Trends in Data

The first factor that may affect the measurement of intensity of lifelog data is the up/down trend of activity, i.e. the quantity of activity either increasing, declining or staying the same within a period of time locally and/or longitudinally. For instance, a triathlete may increase intensity of activity due to the need for intensive training when preparing for competition, or, people suffering from aging symptoms might decrease their overall activity levels due to constrained mobility. The longitudinal or global trend is the trend over a long period of time compared with the local trend which is within a short period of time. Trends can be linear or non-linear but in our experiments we only consider linear trends, which might or might not fit the real world experience, but is easier to illustrate the problem we are facing, namely to compute intensity.

B. Local Activity Patterns

Local activity patterns refer to activity patterns repeated within a short period of time. For example a pattern can be to exercise on Friday and Sunday for 6 months. Patterns can be:

1) Activities repeated on a certain day in a week over a certain period of time such as routine activity on every Monday for a year. In this case, within the one year the intensity of weekly periodicity should remain the same, although the local trend or global trend might change.
2) Activities repeated on any day in a week within a certain period of time. For instance activities that are done once every week for 6 months. In this case we still would like to think the activity is routinely executed, and although on an irregular day but at the same time being done regularly on a weekly basis.

The first situation can be simulated by sampling data using a Gaussian distribution and the second one using uniform distribution. In theory the first would have less randomness than the second because uniform distribution has larger entropy than Gaussian distribution, thus more information is carried.

C. Missing Activity Routine

It is practically impossible in real life to maintain any activity routine without missing some planned activity due to a variety of reasons. The chances that a routine activity would be missed could cause a change of intensity of periodicity. The probability of missing a routine activity thus brings another form of uncertainty into a model of a lifelog. The probability of missing an activity could be as much as a 20% chance that a weekly activity would be missed within a certain month. In other words, the intensity of the weekly periodicity would have been 0.8 of the original intensity if the original routine was kept. We assume the probability of the chance of missing a routine activity follows a uniform distribution.

D. Intensity of Periodicity

Having discussed the factors might change the intensity of periodicity, we have to define what is intensity of periodicity and how can it be computed. Starting from the point where we have already determined which periodicity is significant in our lifelog data, we then compute the intensity of the periodicity. However a key issue is how do we know how "strong" a periodicity is, namely the intensity of the periodicity? The requirement of intensity of periodicity is that it should be able to show:

1) A difference of patterns in terms of quantity. For example two patterns may be the same shape, but with different sizes, and the intensity should show the difference.
2) The integrity of patterns. For instance, two patterns could be the same shape, but only if missing points were filled in. The intensity should be able to show the completeness of a pattern.

Based on these requirements, we find that correlation between the original signal and local patterns could achieve both. In the next Section we will introduce some metrics to compute such a correlation.

E. Metrics for Strength of Periodicity

Since periodicity is observed and significant in almost all lifelog data generated by human subjects, and we suppose we have identified those significant periodicities from a periodogram, we would like to use the lifelog to compute the strength of a certain period at different points in time or for the lifelog as a whole. If we are to compute the intensity change through time, we can use a window and compare the local data with discovered global repeating patterns. The similarity between local data and global patterns is the intensity which could be a correlation or error between local data and the global pattern with a significant periodicity. We use the following notation to explain how we calculate the strength of periodicity. F denotes the DFT [7] of signal $x(n), n = 0, 1, ..., N-1$, and F' denotes the inverse transformation. S stands for the strength of periodicity. We now propose several approaches to calculate periodicity intensity, defined as follows:

$$\begin{aligned} \mathcal{A}_1(k) &= \frac{1}{k}\sum_{n=1}^{N-1} x[n]x[n+k] \\ \mathcal{A}_2(k) &= \sum_{n=1}^{N-1} x[n]x[n+k] \end{aligned} \tag{1}$$

Method 1:

$$\begin{aligned} S &= P(f) \\ P(f) &= \frac{1}{N}\mathcal{F}(x_n)^2 \end{aligned} \tag{2}$$

$$\text{where: } f = \tfrac{1}{day}$$

Method 2:

$$\begin{aligned} S &= P(f) \\ P(f) &= \frac{1}{N}\mathcal{F}(\mathcal{A}_1(x_n))^2 \end{aligned} \tag{3}$$

$$\text{where: } f = \tfrac{1}{day}$$

Method 3:

$$\begin{aligned} S &= P(f) \\ P(f) &= \frac{1}{N}\mathcal{F}(\mathcal{A}_2(x_n))^2 \end{aligned} \tag{4}$$

$$\text{where: } f = \tfrac{1}{day}$$

Method 4:

$$\begin{aligned} S &= max(P(f)) \\ P(f) &= \frac{1}{N}\mathcal{F}(x_n)^2 \end{aligned} \tag{5}$$

Method 5:

$$\begin{aligned} S &= \frac{1}{2}\sqrt{\sum_n (x_n - x'_n)^2} \\ x'_n &= \mathcal{F}'(P(f)), iff \neq \frac{1}{day}, P(f) = 0 \\ P(f) &= \mathcal{F}(x_n) \end{aligned} \tag{6}$$

Method 6:

$$\begin{aligned} S &= CC(x_n, x'_n) \\ x'_n &= \mathcal{F}'(P(f)), iff \neq \frac{1}{day}, P(f) = 0 \\ P(f) &= \mathcal{F}(x_n) \end{aligned} \tag{7}$$

where CC is correlation coefficient.

Method 1 uses the power carried by 1/day frequency as the strength of the circadian periodicity, namely, the correlation between signal and sinusoid with daily periodicity. Methods 2 and 3 use $\mathcal{A}_1$ and $\mathcal{A}_2$ to calculate auto correlation, respectively. Using the result of auto correlation as input to compute the periodogram, we thereafter use power of daily periodicity as strength of the circadian periodicity. It should be noted that $\mathcal{A}_1$ is normalised auto correlation. Method 4 uses the maximum power in the periodogram to represent strength of periodicity, though in this case it is not assured that daily periodicity will carry maximum power all of the time. Method 5 calculates a sinusoid with daily periodicity that is correlated to the data most and then computes root mean square error (RMSE) between the signal and the most fitting sinusoid with daily period. Finally, Method 6 calculates a sinusoid with daily periodicity that is correlated with the data most, and then computes CC between the signal and the most fitting sinusoid with daily period.

If we consider the informal formulation of spectrum estimation as estimating how the total power is distributed over the frequency, the definition of intensity of periodicity can be thought of as the power corresponding to a certain periodicity or to several periodicities. Method 1 comes directly from the definition of power spectral density, which uses DTFT to calculate how power is distributed over frequency directly and here in Method 1 we only take the power carried by 24-hour periodicity. Methods 2 and 3 derive from another definition of power spectrum which shows that spectrum can be achieved as the DTFT of the auto correlation. Method 3 is normally used to calculate auto correlation in signal processing. The reason we also use Method 2 is because when we lag signal to calculate auto correlation, the bigger the lag is, the fewer the number of points that are involved in the calculation. Method 2 tries to eliminate this effect by using averaged value. Both Methods 2 and 3 use power of circadian periodicity as the intensity. Method 4 uses power of frequency with maximum power as intensity. In particular, it is interesting to see a comparison of the result between Methods 1 and 4. Method 5 uses a different way to calculate how the signal differs from the 24-hour periodicity. The rest of the methods use correlation as a metric to quantify the difference while Method 5 uses summed error as the metric to quantify the deviation.

IV. Experiments on Synthetic Data

Experiments are first conducted on synthetic data modelled by the three factors described in Section III with randomness introduced by adding noise at different stages. Assume we are going to simulate N data points where N is a number which is $7\times$ an integral, because we previously discovered a strong weekly periodicity in high-level accelerometer data [6]. The prior is used here and the 7-day pattern is a basic pattern which could compose the whole signal with different scaling and time shifting. The value of N is assumed to consist of local patterns with different sizes. For easy understanding we assume the local pattern is also the integral $\times 7$. The problem can be formalised as: assuming there is a signal $x_n, n = 0, 1, ..., N-1$. The equation to split the signal is:

$$X_m = \sum_n x_n S_n \delta(m-n) \tag{8}$$

where S_t is the function used to split data, δ is a Dirac delta function, and m is the number of segmentations of the original signal. X_m is one segment of the signal. $|X_m|$ is the notation for the length of X_m, namely how many points in each segment. The size of each segment is sampled from a uniform distribution. S_t is a function similar to a window function, but its function is to split the data into local patterns. If we split the data into X_m segments, S_n is defined as:

$$S_n = \begin{cases} 1 & \text{if } n \text{ is in a segmentation} \\ 0 & \text{Otherwise} \end{cases} \tag{9}$$

Each segment X_m is composed of a global trend, local trend and local patterns with missing probabilities. We use the following settings to generate each segment of synthetic data: the size of a segment is chosen from 2 to 10 uniform distributions, which is then multiplied by 7 in order to make a week as a unit of the local pattern. 50 segments are generated. At the stage of generating local and global trends, a linear model $X_m = wn + b$ is chosen as the trend. Parameters w and b from the local linear model are chosen randomly from a uniform distribution range from -0.005 to 0.005 plus Gaussian noise with 0 mean and 0.3 std to the output of the linear model. Finally, the local patterns chosen is a pattern with a weekly repeating period. In order to introduce randomness, the day when the activity is repeated is randomly chosen from a uniform distribution, which means that each day has equal probability of the activity and the day chosen is based on a Gaussian distribution. The quantity of the level of activity is selected from a uniform distribution with range 2 to 7, plus normal distribution with 0 mean and 0.5 std. The probability of missing some activities within each segment is randomly chosen from a uniform distribution range 0 to 1. The intensity of each week is then computed using the quantity of each activity level multiplied by the probability of missing the activity. Figure 1 shows the randomly generated global and local trend data with Gaussian noise, zero mean and 0.3 standard deviation.

Figure 2 shows the result signal with global and local trends, with local patterns. and Figure 3 shows the periodogram for the generated data. Interestingly, we can see that the periodogram is similar to the real data generated by the triathlete described in [6]. The similarity between simulated data and real life data could provide an explanation for the correlation between the time domain signal and spectrum. The power of spectrum in the lower frequency, namely on the left side of the periodogram, indicates the trend of the activity. We can also observe on both periodograms, harmonics on 7-day, 2/7-day and 3/7-day frequencies. It is legitimate to hypothesise that this is caused by regular weekly activity conducted on different days of a week, because this is how we generated the simulated data.

Figure 4 shows the result of using the 6 different methods, introduced in Section III-E, to compute periodicity intensity and the result is compared with ground truth intensity used to generate the data. We can observe that some methods tend to enlarge the peak while some methods are quite close to the ground truth.

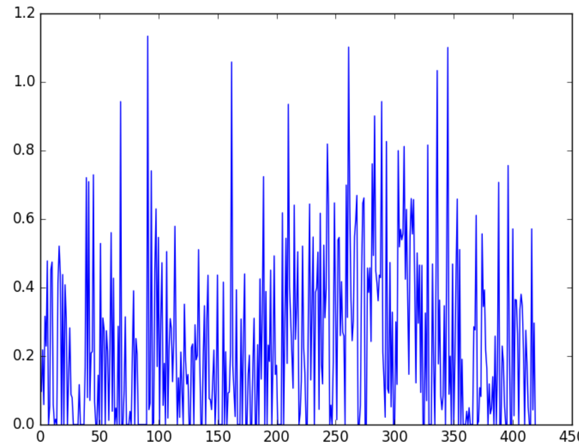

Fig. 1. Global and Local Trend with Gaussian noise

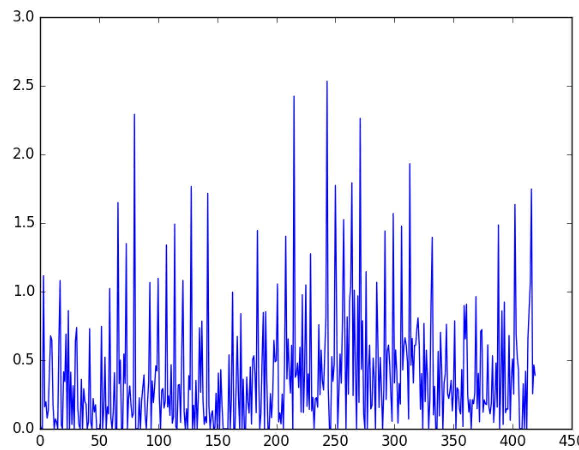

Fig. 2. Signal with Trends and local patterns

In order to evaluate the 6 metrics with more confidence, we ran the randomly generated data for 1,000 iterations and the result is shown in Table I. Performances are evaluated with correlation coefficient (CC) and root-mean-square error (RMSE) between computed intensity using the previously mentioned methods and the intensity used to generate the lifelog data. The window is fixed to 35 days with zero overlap. We compare the result using two different distributions of days, namely normal and uniform. The choice of normal distribution is to simulate the situation that most of the occurrence of an activity is on one day and the distribution of the other days follows a normal distribution. The choice of uniform distribution corresponds to the scenario that activities could be done on any day of a week with equal probability. Not surprisingly, normal distribution has better performance

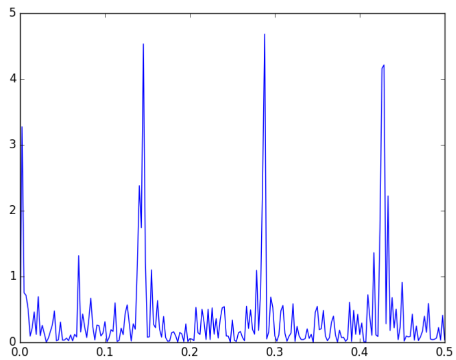

Fig. 3. Periodogram for simulated data. X-axis is frequency and Y-axis is energy carried by corresponding frequency

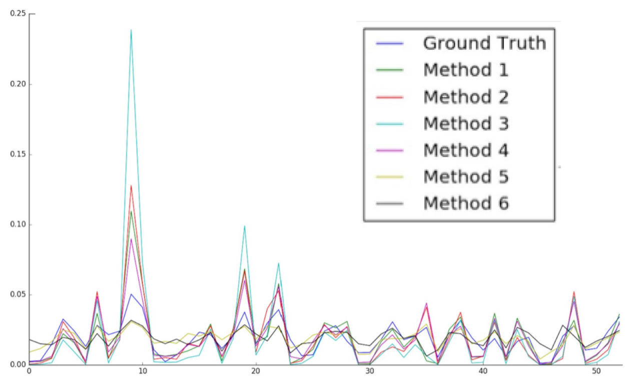

Fig. 4. Periodicity intensity computed with 6 different methods. X-axis is time and Y-axis is intensity of periodicity

than uniform because uniform distributions introduce yet more uncertainties.

TABLE I
PERFORMANCE OF 6 METHODS AS MEASURED BY CC AND RMSE

		CC		RMSE	
Distribution	Method	Mean	Std.	Mean	Std.
Normal	Method 1	0.791	0.053	0.0015	0.0002
	Method 2	0.757	0.057	0.0017	0.0002
	Method 3	0.725	0.056	0.0027	0.0005
	Method 4	0.827	0.044	0.0011	0.0002
	Method 5	0.740	0.059	0.0009	0.0001
	Method 6	0.677	0.083	0.0009	0.0002
Uniform	Method 1	0.747	0.063	0.0017	0.0003
	Method 2	0.763	0.059	0.0017	0.0003
	Method 3	0.700	0.062	0.0029	0.0006
	Method 4	0.832	0.042	0.0011	0.0002
	Method 5	0.741	0.059	0.0008	0.0001
	Method 6	0.576	0.098	0.0011	0.0002

Figures 5 and 6 show the correlation coefficient between computed intensity levels using different metrics and the intensity used to generate the lifelog data. The X-axis is the window size with a unit of one week. Note that the starting of window size is 1 week which corresponds to 0 on the X-axis. We can see that the CC changes with the window size. The CC increases with increase of window size at the beginning but at a certain point the CC does not improve as we continue to increase the window size. For some metrics, performance even decreases. Figure 5 used normal distribution to generate the day on which activities would be conducted. In this setting, the performance of CC tends to converge at a window size of 4 or 5 weeks. Figure 6 uses uniform distribution to generate the day on which activities would be done. A similar trend can be observed in both figures.

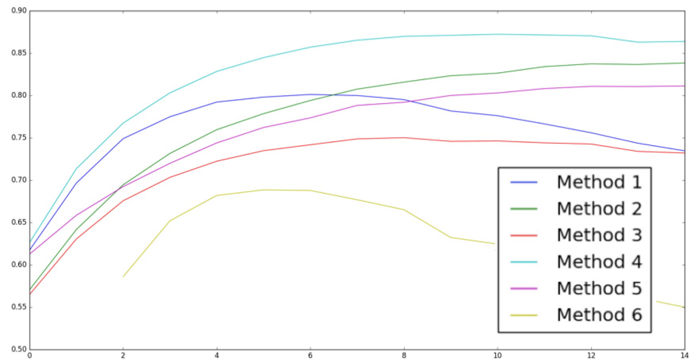

Fig. 5. CC trend with window size changing using normal distribution. X-axis is window size. Y-axis is pearson correlation between a method and ground truth.

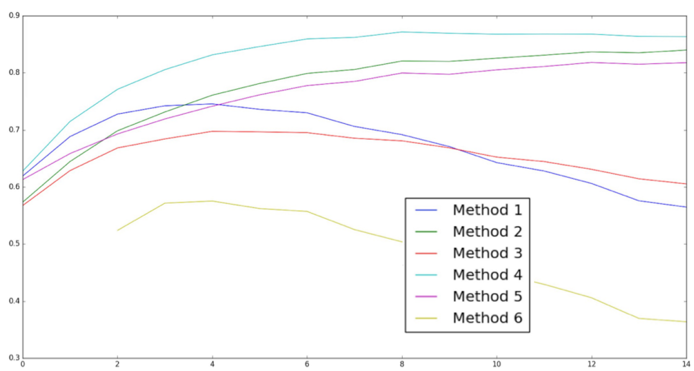

Fig. 6. CC trend with window size changing using uniform distribution. X-axis is window size. Y-axis is pearson correlation between a method and ground truth.

V. WORKING WITH REAL LIFELOG DATA

A. *The ASU Dataset*

The Arizona State University (ASU) runs a program to monitor sleep quality for US Veterans. The target population in the study was US Veterans currently receiving clinical care at a regional Veterans Health Administration (VHA) hospital in the Southwestern United States, aged 35-65 years, measured as either overweight or obese. Eligibility criteria for the study also included reporting of insufficient physical activity, excessive sitting, and short sleep duration ($<$ 7 hours/night) or mild/moderate sleep complaint (modified version of the Insomnia Severity Index [ISI] by [8]). Participants were initially screened by telephone followed by an in-person visit to confirm eligibility and to complete informed consent procedures. At this visit participants were given a wrist-worn accelerometer to wear for 3 consecutive weeks. This period constituted the "run-in" period of a behavioral intervention and baseline data collection. Participants were asked to wear the monitor continuously during both sleep and wake and to self-monitor their sleep, sedentary, and active behaviours using a customised smartphone application. After two weeks, participants were mailed a second accelerometer and asked to return the first accelerometer in a pre-paid envelope. At three weeks participants returned for a second in-person visit where the second accelerometer was returned.

Following this visit, participants were randomised to receive active elements of the behavioural intervention. A full description of the intervention can be found in the work by [9], but briefly, participants were randomised into an experiment where smartphone-based interventions targeting sleep, sedentary behaviour, and physical activity were delivered for 8 weeks. All participants maintained self-monitoring of their behaviours using the custom application during the intervention phase. Participants also attended two additional visits during the eight weeks to complete study-related assessments and to return/exchange accelerometers to maintain continuous wear and data collection. During the data-gathering, movements during sleep and wake by participants were monitored objectively and continuously throughout the study period using the GENEactiv accelerometer. The GENEactiv is an open source, wave-form wrist-worn accelerometer that is fully waterproof, allowing the monitor to be worn continuously, 24 hours a day without the need to be removed during water activities. Since the GENEactiv provides continuous forms of data recording for periods of at least 1 month it can be considered a valid form of lifelogging. Data captured on board the device were initially sampled at 40Hz and summarised to 1 second epoch using a gravity-subtracted sum of vector magnitudes.

The ASU data is a dataset which contains data on more than 25 individual subjects, each wearing a wristband wearable sensor freely for several weeks without interruption. The dataset includes data gathered by an accelerometer, luminance, temperature, voltage of the device itself and all these are timestamped, but in our work only the 3-dimensional accelerometer data, and its timestamp, will be used.

To take advantage of the continuous and longitudinal nature of the data, the full accelerometer data for the run-in and intervention periods were used in our analysis and data was cleaned by removing overlap data (when more than one accelerometer was worn during changeover periods). Despite being asked to wear the accelerometer continuously, there are gaps and missing days or days which might not contain useful information because the subject may have felt uncomfortable wearing it, or forgotten to put it on. Such days normally have low information entropy, so we manually examined entropy curves for each subject and determined an entropy threshold for each subject. This corresponds to a personalised threshold of activity level, per subject. We then only use days which have an entropy value larger than the threshold as our training and testing set.

The ASU dataset poses some interesting possibilities for periodicity detection which may improve or disimprove before or after the sleep intervention that each subject was given at different points during the study. It will be interesting to examine this to see if the intervention has an impact on the regularity of the lifestyle and behaviour of participants, as indicated by the strength of periodicity over time.

B. The Athletic Dataset

This dataset represents a 10-year record of physical exercise and training activities including running, cycling and swimming, from an international triathlete now retired from competition. The log contains a daily entry for distance covered for 1 or more of the three sports as well as daily text comments to indicate mood, training effort, relative performance, weather, etc. and these can be analysed for sentiment. This sports dataset captures 100% of activity log in the 10 years, i.e. there are no missing entries and the log is complete.

Obvious periodicities which could be detected from this data include seasonal performance at targeted sports events, perturbations caused by occasional injury and overall decline over the decade from aging.

VI. Experiments on Real Data

We now present the experimental results for calculating periodicity intensity on two real lifelog datasets.

A. Experiments on the ASU data

We computed the longitudinal intensity of periodicity using the ASU data introduced previously. To explain the results we obtained more concretely, we use one participant, number 102, shown in Figure 7 and we outline our methodology for identifying periodicities and visualising periodicity strength. In Figure 7 we see 4 sub-figures, A, B, C and D. Panel A provides a visualisation of the sum of vector magnitudes (at 1 second epoch) along the Y-axis and time along the X-axis over the course of the 12 week monitoring period. Sleep and wake periods are evident visually. The raw data from the accelerometer was summarised to 1 second epoch using the gravity-subtracted sum of vector magnitudes. This plot of the overall activity levels illustrates several isolated periods of high activity, probably exercise of some form, throughout the 12-week period but there is no evidence of changes in behaviour.

Panel B displays a periodogram calculated from the 1 second epoch. Here, the X-axis is frequency and Y-axis is energy of the frequency, namely, how strong the corresponding frequency is. This shows a reasonably strong energy level around the 1-day point and a smaller peak at around the 12-hour point which is the harmonic of the circadian. No within-day or weekly patterns were observed. 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 disorganised and irregular lifestyle.

Panel C plots time (X-axis) by the strongest periodicity observed over the 3-day time lagged window. The Y-axis of panel C is the frequency that carries maximum power within a window. In this example, the 24 hour periodicity held consistently for the majority of 3-day windows with small breaks at the beginning of the monitoring period.

Panel D describes the strength of the periodicity using Method 1 (Y-axis) over time (X-axis). The strength/intensity of the 24 hour circadian periodicity changes throughout the lifelogged observation period, showing, for example, a weaker period of regular circadian cycle from week 5 to week 6 and again from around week 10. This reveals a behaviour change during those days not at all visible or discernible from raw data and a clinician or other health professional could help to interpret this change and whatever caused it, perhaps an intervention of some kind.

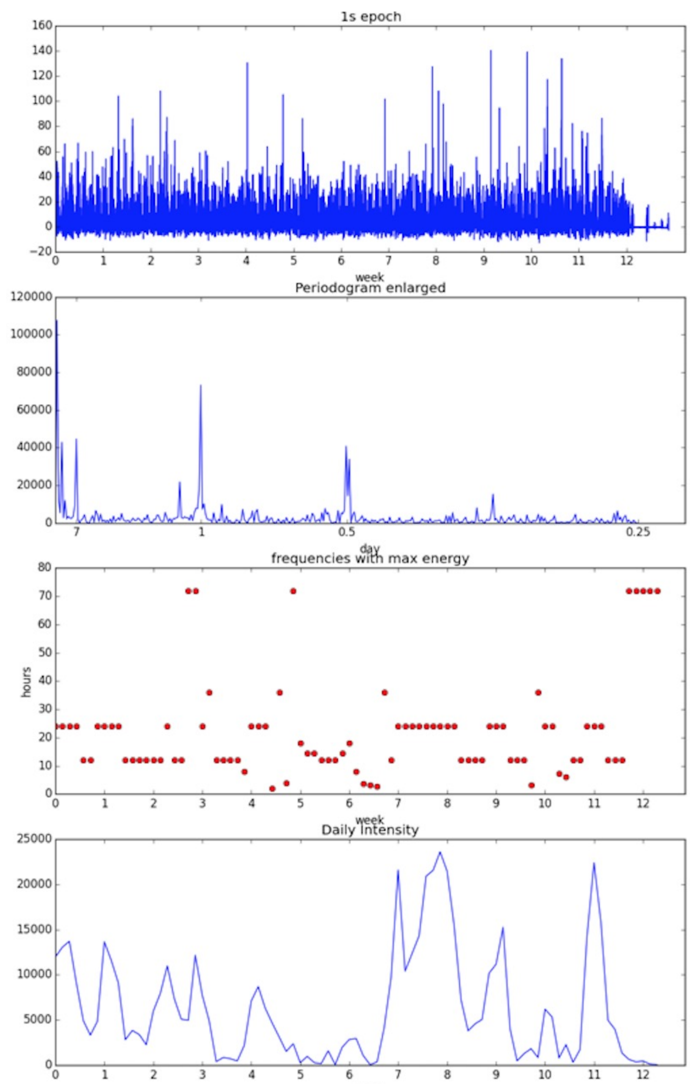

Fig. 7. Results for ASU Data Subject 102. X-axis and Y-axis of panel A is time and 1 second epoch. X-axis and Y-axis of panel B is frequency and energy. X-axis and Y-axis of panel C is time and frequency that carrying maximum energy. X-axis and Y-axis of panel D is time and periodicity intensity.

We also computed the longitudinal intensity of accelerometer data periodicity using Methods 1 to 5 for every subject and part of the result is reported in [10].

B. Experiments on Athletic Data

The Method 1 metric with a 28-day window and zero overlap is used to show example results on the Athletic data, introduced earlier and Figures 8, 9, 10 and 11 present these results. The intensity result is normalized by the sum of the intensity data series. The reason for selecting a 28-day as window is because this window size showed some good quality in the simulated experiments described in Section IV.

In Figure 8 we can see several running patterns in the periodicity intensity graph. For example there are peaks at the beginning of 2004 and 2006 and at the end of 2008 and beginning of 2009. Generally speaking, intensity increases until 2007 where it maxes and then starts to decrease. In Figure 9 we show the intensity of weekly periodicity for cycling. We see the subject started to cycle from 2007 onwards and the intensity level increases until 2014 when there is a sudden decrease. In the middle of 2010 there is very high intensity. Figure 10 for swimming shows fewer changes compared to running and cycling but still we can see peaks at around the beginning of 2008, the end of 2009 and the end of 2012 / beginning of 2013. In aggregated data shown in Figure 11, peaks seems repeated with a period of 2 years.

To help interpret these findings, the most discernable patterns were identified and presented to the participant in a focus group interview where most of them were validated and an explanation for each was offered, though some of the patterns were new insights that the subject was not aware of.

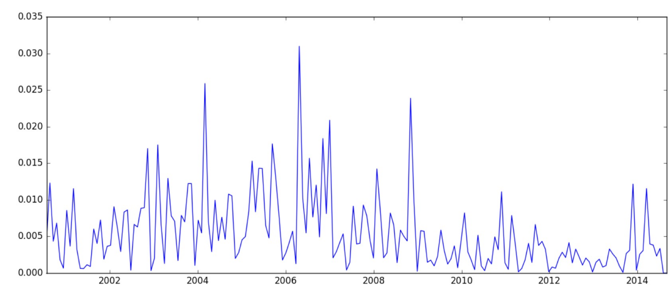

Fig. 8. Periodicity Intensity Graph for Running Data. X-axis is time and Y-axis is periodicity intensity.

VII. Discussions

In this paper we studied the intensity of periodicity as it appears in lifelog data and we proposed several methods to calculate the intensity of periodicity over time. Because longitudinal lifelog data is so difficult to use for research purposes we proposed a model to generate it and we used generated data in our first set of experiments. Some of our methods for measuring periodicity intensity were then executed on real life high-level and low-level lifelog data.

In the model we proposed to generate high-level lifelog data, we considered factors including global trends, local trends,

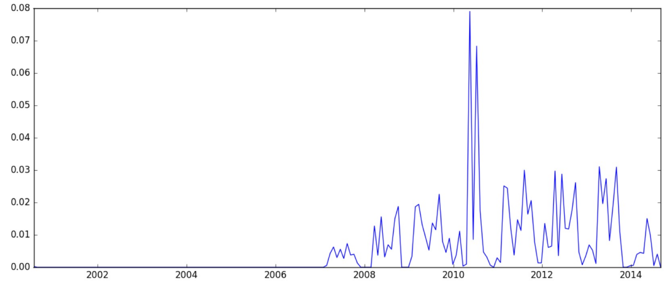

Fig. 9. Periodicity Intensity Graph for Cycling Data. X-axis is time and Y-axis is periodicity intensity.

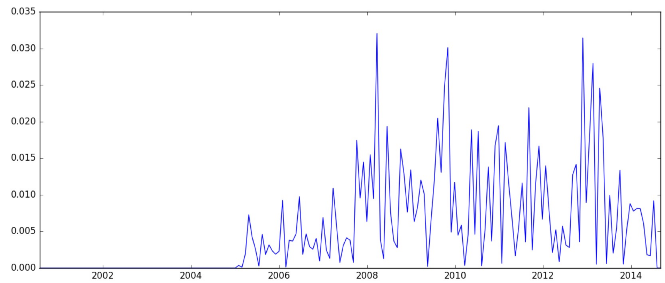

Fig. 10. Periodicity Intensity Graph for Swimming Data. X-axis is time and Y-axis is periodicity intensity.

local patterns, and the probability of missing activities, i.e. some activities not being logged or recorded. Each factor is determined by further parameters with introduced randomness. We use known intensity which is also randomly generated, to simulate high level lifelog data allowing us to compare the performance of different periodicity intensity metrics against the intensity used to generate data and we observed how changing window size can affect the performance of those metrics. We firstly compared periodograms from simulated data and real high-level lifelog data, and discovered similarities between them.

Different methods for computing periodicity intensity performed on generated data achieve similar results. In general, Methods 1 to 5 show quite correlated results compared with the intensity used to generate the lifelog data for both uniform and normal distribution of days. In experiments to find correlations between window size and performance, we explored different window sizes. We discovered that performance increases rapidly at the beginning, but after window size exceeded ca. 4 weeks, the improvement in the performance tends to be stable, and for some methods even to decrease.

We also conducted experiments on real lifelog data where experiments conducted on the Athletic data also revealed some of the intensity for each sporting event that the triathlete trains for. The experiments we conducted on real lifelog data naturally lead to the next step which would be further exploration of the results with the subjects involved in the experiments. In the case of Athletic data we interviewed the subject who confirmed an explanation for most of the changes in periodicity intensity we observed as well as revealing new

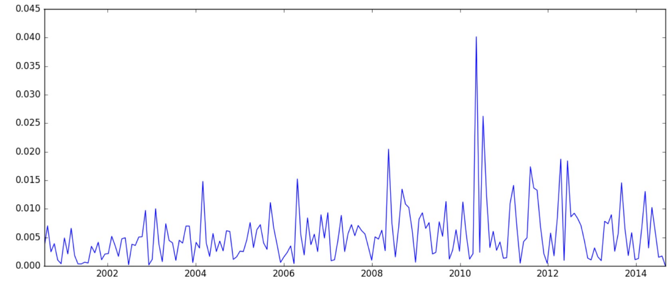

Fig. 11. Periodicity Intensity Graph for Aggregated Data. X-axis is time and Y-axis is periodicity intensity.

insights not previously known. For the ASU data we have fed the insights gained from our analysis back to the clinicians in charge of the ASU study to see if shifts in periodicity intensity correlate with the sleep interventions they introduced but the results of this are not known yet.

Acknowledgments

The authors thank Science Foundation Ireland for funding under grant number SFI/12/RC/2289, the Virginia G. Piper Charitable Trust, the ASU/DCU Catalyst Fund, and the European Community 7th Framework Programme (FP7/2007-2013) under grant agreement 288199 (Dem@Care).

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