Wrist Actigraphy Analysis From Motionwatch8 Data

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***Abstract*—This article expands the presentation made at SENSORDEVICES 2018. The author makes available to the public one year of wrist actimetry in real life, stored at one second epochs. The technical details of the system used (Motionwatch8) are described and they show why quantitative methodologies applied to actigraphy are tied to the system used for data acquisition. A first evaluation of that data calls for new ways for actimetry analysis and actigraphy display. Most of the values recorded are equal to zero and therefore the information they provide is a main target for actigraphy analysis. It is explained the difference of the quantity of zeros epochs when one second and one minute epochs are used. Series analysis and percent of zeros parameters are proposed and exemplified. In particular, the analysis of series is a new area of studies for actigraphy because it changes the meaning of the data recorded. The daily pattern of series is constant along the year and the importance of long zero-series is underlined: that small percent of lengths is not distributed randomly. The analysis of series also suggested the idea that the couples of series, not the single series, could be functionally similar and a actigraphy "pulse" analysis could be worthwhile to further evaluate. The percent of zeros parameter is applied to long and short time intervals and it could be a complementary tool for wake-sleep studies. The research described in this article is a ground breaking type of work that creates new questions more than providing answers, but it already offers new insights on actigraphy data.**

Keywords – Actigraphy; Actimetry; Motionwatch; Network physiology; Rhythms; Symbolic dynamics.

I. Introduction

This article expands the presentation made at SENSORDEVICES 2018, the Ninth International Conference on Sensor Device Technologies and Applications [1], adding details on the system used, the analysis suggested and some preliminary results.

Wrist actigraphy has a long history that starts in the 1950's and develops until today with research and clinical applications [2]. The terms "actimetry" and "actigraphy" are used as synonymous for motion activity measures where "actimetry emphasizes the measurement aspect of the technique and actigraphy emphasizes the descriptive aspects of the technique" [3].

Clinical guidelines and researches suggest that wrist actimetry is particularly useful in the documentation of circadian rhythms, of sleep disorders, of treatment outcomes and as an adjunct to home monitoring of several pathologies. During the day, it is possible to quantify the physical exercise and (with calibration) recognize some type and intensity of the exercise. Reviews are available in several application areas [4]-[8].

Most published data use a one minute epoch, i.e., the system stores one piece of data each minute, and recordings are limited to a few days. The reasons for that selection of parameters are mainly practical, due to the characteristics of the available instrumentation and the logistic/organizational issues of the recordings, especially in real life. That selection of parameters sets limits on the possible evaluations of the data. Shorter epochs of actimetry could allow better correlations when the data is used for wake/sleep studies because the "gold standard" reference is the polysomnography (PSG), where data is presented in pages 30s long with signals in the range of 0-100 Hz. Without long continuous recordings, it is unknown if and how much Infradian rhythms, maybe spanning over years, have an impact on the evaluation of shorter recordings. The technology advances offer today the possibility to record more data and in an easier way, but still few long term recordings are described in literature [9]-[15] and only few groups explore shorter epochs [16]. None of those "extended" recordings are available to the public. To explore those two areas, the only option is to make longer recordings with shorter epochs and here we describe one of them that the author published on the National Sleep Research Resource (NSRR) platform [17]. That data expands the universe of wrist actigraphy both in length (from week to years) and in granularity (from minutes to seconds).

Section II describes the modality of the recording, the export of the data from the original format and the assembling of an activity file of one year.

Section III explains why each brand and each model of actigraphic systems needs its own computation of numerical data.

Section IV describes the main characteristic of the data, options to study it and the most important findings of those preliminary results.

Section V recaps the methodology issues and we conclude our work in Section VI.

Unless otherwise noted, the data used are those recorded by the author and available to the public [17]. Computations were made with the software Motionware (V.1.1.16) from CamNtech Ltd (Cambridge, UK), the manufacturer of the Motionwatch8 (MW8) activity monitor used for the recording [18], or by programs written by the author in Octave [19]. When data outside the published year is used, raw data are available from the author on request.

II. Materials and methods

The subject of the recording is the author: age 62 at the start of the recording, male, BMI= 26.3, no known major chronic pathologies. Data is collected using a MW8 on the non-dominant wrist. MW8 is a clinical system extensively used and it is a recognized reference in the field [20]. The monitor is set to store data in an epoch of one second in "normal" mode. That means that the intensity of the movement on the axis perpendicular to the surface of the unit, is measured by an accelerometer sampled at 50 Hz. Data is transformed in a single value of a custom unit (Counts) each second. The monitor acquires also a value of light intensity (Lux) each second. Details are described elsewhere by the manufacturer [21]. A maximum of 36 hours of activity and lights data is stored at 1s epoch in the unit and therefore there is the need for a data download every day. A diary is kept of major events (travels, flu, mismanagement, etc.). As usual in this kind of recordings, it is not possible to know the exact position of the unit on the wrist and if and when the photocell of the unit somehow was obscured (garments, tools, etc.).

The marker available on the logger is used to signal when the unit is not worn. Using the MotionWare software, the values inside the marked intervals are modified from 0 to “n/a”. Then, the recordings are joined in files containing more or less 10 days (one million lines) and exported as .CSV files. Using a spreadsheet (OpenCalc – Apache OpenOffice – Apache Open Foundation), lines “n/a” are changed to “-1” and the data is divided in 9 columns: year, month, day, hour, minute, seconds, counts, lux integers, lux decimals. That format allows the files to be easily accepted by several software programming languages.

With programs we wrote in Octave, activity Counts are extracted, saved as .MAT files and joined in one year long file, for a total of 31.576.501 data lines. The time of the file is continuous, aligned to “summer” time (UTC+2: 27 March to 30 October 2016; 26 March to 29 October 2017) used in Italy in June, at the beginning of the recording. Evaluations and graphics of this article are computed from that file using programs we wrote in Octave.

III. Raw Data

This paper works over the data acquired with the activity monitor model Motionwatch8 (MW8) from CamNtech Ltd. It is not possible to directly compare the numbers out of that unit with other models or brands because each system has his own way of data acquisition, a well known situation not improved in the past 20 years [22], as described below.

A. Analog Band-pass.

At the end of last century few systems for wrist actigraphy were used, like the Geweiler from Sing Medical, Aktometer from ZAK, Actiwatch from Cambridge Neurotechnology, Motionlogger from Ambulatory Monitoring Instruments (AMI) and Colburn from IMSystems and they used different approaches. For instance, AMI offered a system with selection of ranges from 1 to 9 Hz and the Actiwatch used a 1-6 Hz bandpass. [23]. Observations from the group of Van Someren [24] started a change that moved Actiwatch to the bandwidth 3-11 Hz. Today, AMI product range is on a 2-3 Hz band-pass while CamNtech Ltd (heir of Cambridge Neurotechnology) stays on the 3-11 Hz. For other systems available in the market today, the band-pass seems an “implicit” value, not described in user manuals, white papers or “validation” studies. The issue seems not of interest both from a marketing and from a clinical point of view, meaning that the value is not even mentioned [6],[25].

B. Sampling.

Sampling rates of professional systems available in the market today, range from 30 to 256 Hz, the intensity range of the accelerometer is typically +/- 8G and quantisations used are from 8 to 12 bits. After sampling, the systems set a threshold in order to remove “noise” from different sources and below that level a 0 value will be stored.

C. Data reduction.

Data reduction is a common issue for many biological signals and especially for sleep, caused by the ability to collect much more data than humans like to manage. Old professionals that remember ink and paper polysomnography will probably also remember their old professor boasting that he was able to “read” recordings just looking on the side of the paper batch. It was a simple analog data reduction of more than 100 times because it was one line every two pages of 30 seconds data. For the MW8, the data reduction is made on line when only the maximum of the 50 values sampled each second is stored [26]. That decision implies the assumption that if there is some movement inside the second, then the integral of the movement will be a constant multiple of the peak value. In other words, that the integral of the movement will be similar to that of a rectangular form that changes only one side but not the other. An assumption without a published demonstration, but that is “good enough” from the manufacturer evaluation (personal communication). Those are the “raw data” available. A second step of the data reduction, possible on or off line, is the use of longer epochs, which is the sum of the one second values over an interval. If we use an epoch of 30 sec in the system settings, that will provide a number every 30 sec that become the raw data available out of the system.

With the situation described above, the algorithms used for data evaluation are tied to the individual system.

D. Measurement error.

The Micro electronic mechanical systems (MEMS) technology used today inside actigraphs does not suffer of the aging, lost calibration and inter system calibration differences as much as the old piezoelectric sensors. The calibration of systems (acceleration measurement) from the manufacturing is inside a +/- 5% for 1g (personal communication) and MW8 has an expected lifetime of 7 years without the need of any further calibration.

Unfortunately, the most important expected error is not coming from the instrument, but from its positioning. Even if the oval design of the MW8 is a nice improvement over the squared models of the past, displacements along and around the wrist are still possible. Those displacements create a fluctuation from what would be the measurement if the system could be placed always in the same position for the full recording. We did not find any published paper regarding that issue. Most published articles that discuss and "validate" algorithms simply does not include the topic. So we set up a recording of two units on the same wrist for one month. It is not the best way to measure that error because the presence of a second unit by itself creates a bias. A better option would be to setup a grid of sensors around the wrist that covers all possible positions and then check the relationship among them. The development of such a grid would be useful also for other researches on the kinematics of the wrist. However, with the two recorders at least we get a dimension of the issue. Relative position, case and strap of the two instruments were randomly exchanged during the daily data download, trying to minimize the error sources different from the change of position on the wrist.

Table I shows the comparison of the results of the sleep analysis for the two units performed by the Motionware software out of 34 nights. Note that in order to compute the sleep analysis the Motionware software uses 30 sec epoch, summing up the 1 sec raw data.

Table I. Co-recording of two MW8 on the same wrist of 34 nights. Max positive, max negative and mean absolute differences of sleep analysis parameters between the two units.

	POSITIVE MAX DIFF	NEGATIVE MAX DIFF	TIPICAL VALUE	MEAN ABS DIFF
Lights out				
Fell asleep	00.08.00	-00.08.00		00.00.53
Woke up	00.13.00	-00.06.00		00.01.11
Got up				
Time in bed				
Assumed sleep	00.13.00	-00.07.00	06:31	00.01.44
Actual sleep time	00.12.00	-00.16.00	06:00	00.06.18
Actual sleep (%)	2,7	-3,7	92,1	1,3
Actual wake time	00.21.00	-00.12.00	00:31	00.06.21
Actual wake (%)	3,7	-2,7	7,9	1,3
Sleep efficiency (%)	2,5	-3,2	90,4	1,3
Sleep latency	00.08.00	-00.08.00	00:06	00.00.53
Sleep bouts	12,0	-7,0	30,0	2,9
Wake bouts	11,0	-7,0	30,0	3,0
Mean sleep bout	00.03.28	-00.02.41	00:12:01	00.00.50
Mean wake bout	00.00.44	-00.00.20	00:01:02	00.00.09
Immobile mins	12,5	-10,5	365,5	3,1
Immobile time (%)	1,3	-1,2	93,4	0,5
Mobile mins	7,5	-5,0	26,0	2,4
Mobile time (%)	1,2	-1,3	6,6	0,5
Immobile bouts	14,0	-5,0	38,0	2,8
Mean immobile bout	00.01.11	-00.01.58	00:09:37	00.00.29
Immobile bouts <=1min	4,0	-5,0	4,0	1,5
Immobile bouts <=1min (%)	5,9	-12,4	10,5	2,5
Total activity score	3198,0	-2344,0	2107,0	917,4
Mean activity /epoch	2,9	-2,3	2,7	1,0
Mean nonzero activity /epoch	24,2	-26,8	40,5	8,7
Fragmentation Index	5,7	-11,6	17,2	2,7
Threshold				
Rest per 24h (%)	3,7	-5,7	62,7	2,0
Average light (lux)	3,7	-0,4	0,2	0,5
Central Phase Measure (min)	7,5	-4,0	249,8	1,1

For each parameter, in Table I it is shown the maximum positive and negative difference, a typical value (in order to provide the reader with a relative dimension of the differences) and the mean of the absolute difference for all the nights.

Motionware software, offers also the statistics Non Parametric Circadian Rhythm Analysis (NPCRA) and 24h Average, as shown in Table II.

Table II. Co-recording of two MW8 on the same wrist of 38 days.

NPCRA Statistics:		
Start hour of analysis	11/08/2018 01:00	11/08/2018 01:00
Length of analysis	38 days, 9 hours	38 days, 9 hours
L5 Average	742	705
L5 Start Hour	01:00	01:00
M10 Average	8917	8878
M10 Start Hour	07:00	07:00
RA (Relative Amplitude)	846	853
IS (Interdaily Stability)	453	456
IV (Intra-daily Variability)	1115	1171
24h Average Statistics:		
Start time	00:45:00	00:46:00
End time	09:39:04	09:36:40
Start date	11/08/2018	11/08/2018
End date	18/09/2018	18/09/2018
Daytime Average Activity	2.6 MW counts	2.6 MW counts
Nighttime Average Activity	0.8 MW counts	0.7 MW counts
Day/Night Average Ratio	3.38	3.61
Fitted Cosine Peak	13:53:21	13:52:05

In this case all 38 days were used, including 4 days not fully co-recorded due to management mistakes, therefore adding more variability. Even so, the differences are minimal. If we perform those analyses over one week we find Table III, where there are some differences.

Table III. Co-recording of two MW8 on the same wrist of 8 days.

NPCRA Statistics:		
Start hour of analysis	10/08/2018 00:00	10/08/2018 00:00
Length of analysis	8 days, 0 hours	8 days, 0 hours
L5 Average	727	790
L5 Start Hour	00:00	00:00
M10 Average	7141	7405
M10 Start Hour	11:00	08:00
RA (Relative Amplitude)	815	807
IS (Interdaily Stability)	586	535
IV (Intra-daily Variability)	1342	1282
24h Average Statistics:		
Start time	00:00:00	00:00:00
End time	00:00:00	00:00:00
Start date	11/08/2018	11/08/2018
End date	18/08/2018	18/08/2018
Daytime Average Activity	2.3 MW counts	2.3 MW counts
Nighttime Average Activity	0.6 MW counts	0.6 MW counts
Day/Night Average Ratio	3.99	3.82
Fitted Cosine Peak	14:53:05	14:32:16

Those tables suggest that the error due to the movement of the instrument itself has a different importance for each parameter, depending on the length of the recording.

IV. RESULTS

Out of 31,576,501 samples, there are 24,936,212 zeros (78.97%), 1,034,485 n/a (3.28%) and 5,605,804 (17.75%) non-zero values. If we compare data stored at one second epoch with data stored at one minute epoch (most used epoch in published articles), we find a completely different ratio between zero and non-zero samples. Over the 1440 minutes of a day, a typical result for one minute epoch would be 555 (39%) zero and 884 (61%) non-zero epochs while for the one second epoch, zeros are about 80 % of the total. How is that possible? The answer is that one minute epochs are computed as the arithmetical sum of 60 one second samples and most of those samples are zero. For instance, in the lower line of Figure 1, minutes 02.41, 42 and 43 would be counted as 3 active minutes using a one minute epoch, while there are only 5 seconds of detected movements.

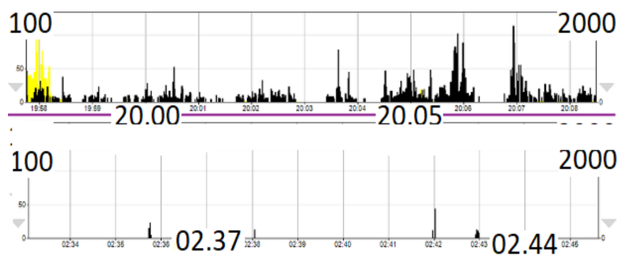

Figure 1. Examples of recordings at epochs of one second: day upper side, night lower. Actimetry in Counts (black) with range on the left, light in Lux (yellow) with range on the right.

Since the large part of the samples are zeros, we need to extract information also from those zero values. Here below we discuss some new possibilities.

A. Series analysis

One option for data analysis of zero values could be to show not the single epoch values, but the length of the succession of series of zero and non-zero values. For instance, the sequence ...,0,m,n,0,0,0,p,q,r,0.... will be described using positive and negative integers as …,2,-3, 3,...

In the recorded year, there is a sequence of 1.429.113 zero series and, of course, the same amount of non-zeros ones. The distribution of lengths of series at one second epoch in the year is shown in Figure 2, with non-zero series on the right and zero series on the left. The zero series can be long up to 7400 seconds, the non-zero series up to 623 seconds. There is a peak of several hundred thousand series around few short lengths.

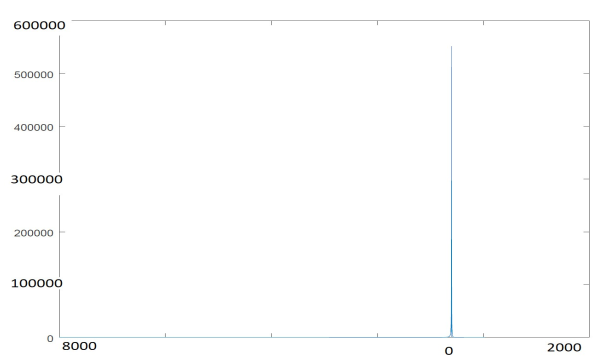

Figure 2. Full year. X axis: length of the series. Zeros series on the left, non-zero series on the right. Y axis: number of series.

If we zoom in Figure 2, we see (Figure 3) that, over one year, the number of zero and non-zero series longer than 10 seconds is a small percent of the total. But, that small percent of lengths are not distributed randomly. When we plot the series, with the length of non-zero series up and that of zero series down and the distance between the series equal to the length of the series, we get a graph as shown in Figure 4.

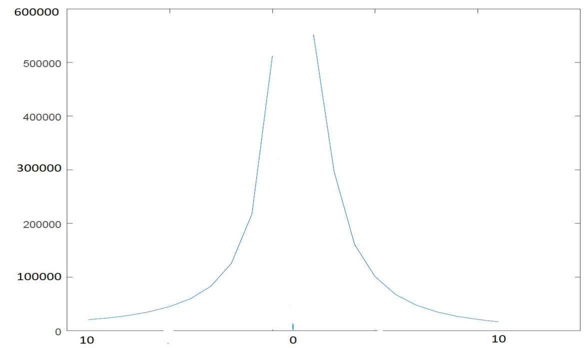

Figure 3. Full year - Zoom of Fig.4 X axis , zeros series on the left, non-zero series on the right Y axis– number of series.

The pattern is clearly bimodal and that daily profile is consistent over the year.

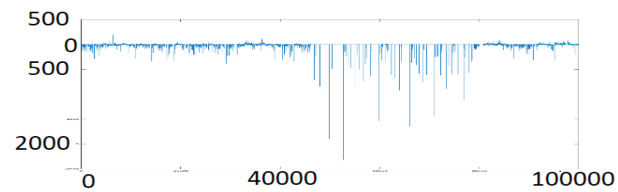

Figure 4. Day one, Start time 09:52:00. X axis: 100,000 seconds – Y-axis: length of the series in seconds: non-zero series up, zero series down.

We may then try studying those series as states of a system and search for models of their dynamics. For instance, we may evaluate one step from zero series or from non-zero series. If we plot the length of zero series as negative values and non-zero series that follows them as positive, as in Figure 5, we see that only short zero series can move to long non-zero ones.

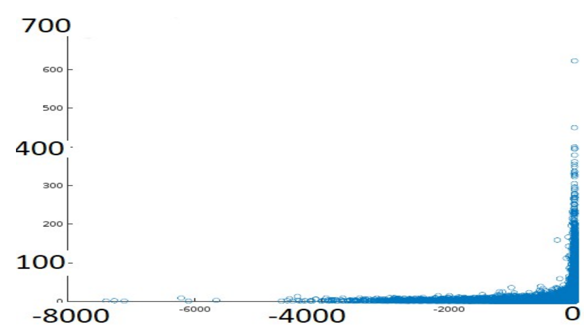

Figure 5. Full year. X axis: zeros series, length in seconds. Y axis : non-zero series that follow, in seconds.

In the same way, Figure 6 shows that only short non-zero series can move to long zero ones. This suggests, for instance, a model like the one in Figure 7 and the possibility to make statements on the data dynamics without any a priori hypothesis.

We know from Polysomnography (PSG) that the body activity changes during those long zero series because they cover different sleep stages and we then try to further investigate those long zero series. The year of data available on the NSRR platform is part of a larger project [27]. The recording started 6 months before of the published year and the internal report of those first six month is public [28].

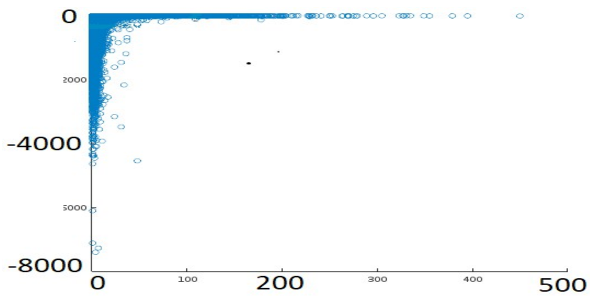

Figure 6. Full year. X axis: non-zeros series, length in seconds. Y axis: non-zero series that follow, length in seconds.

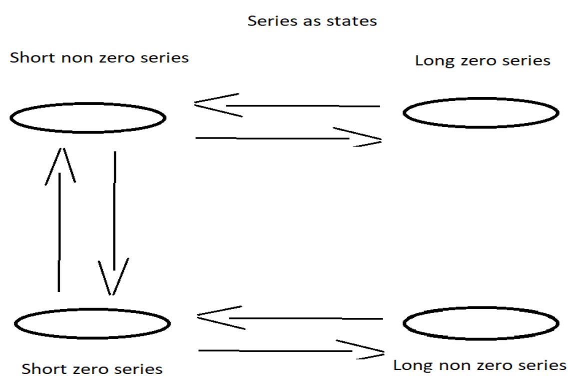

Figure 7. Model of series as states.

On the data recorded during the first month (27 days, one minute epoch) the minimum value of the longest zero succession of each night was 30 minutes, i.e., each night there is a zero-series long at least 30 minutes. Let's call D1 that group >=30 minutes. More than one series of that D1 group can be found in a night, up to four in that month. We may replicate the procedure (i.e., at least one value each night) below the D1 level and get two more groups: D2, from 16 to 29 minutes and D3, from 9 to 15 minutes.

If we add the hypothesis that all the D1 series are functionally similar, we may sum them and found a mean value of the total of a night of about 100 minutes. As described in that report [28], the analysis of the following 5 months (one minute epoch) afterwards demonstrated that there are nights without D1 series and the total D1 time in a night may vary from 0 to more than 230 minutes. More important, D1 series were possible only during sleep (personal communication). It was a first rough evaluation, but the hypothesis that long zero series are linked to physiology was worth to consider.

In a complex system like the human body, it is naive to think to find a fixed value for a threshold. It is more probable that the threshold, if it really exists. is fluctuating over time. For the moment, the fixed thresholds of D1 and D2 will provide a gross evaluation and if we evaluate D1 and D2 along the year we find a further support to the idea of two "types" of series hidden inside the D1-D2 ranges. We may sum day after day the length of the D2 zero series of the year and compare the real increment with a theoretic linear one. For a better display the linear sum is used as the zero axis and we get Figure 8. We keep the convention that zero series are a negative number. When the line is on the positive side, there is a cumulative shorter amount of D2 compared to the theoretic linear sum of the daily mean. When the line of the graph increases then that day there is less D2 then the theoretic linear mean.

Figure 8 shows a very small fluctuation similar to a bimonthly rhythm. The D2 daily mean is 6680 seconds and the mean length of a series is 1263 seconds, so about 5 series are needed each night.

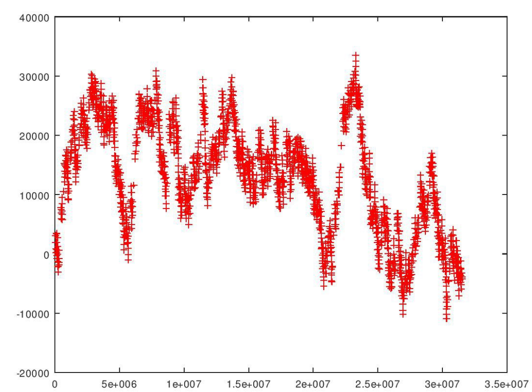

Figure 8. Difference of the D2 Zero Series sum less the linear sum of the mean along the year. X axis seconds from recording start, Y axis difference in seconds. Starting date 17 June 2016, near the summer solstice.

If we plot the values of the D1 series over the published year (Figure 9), we see that only few of them are longer than 5000 seconds (about 80 minutes), with a series mean of 2466 seconds. The daily mean is 4865 seconds, so one series is usually not enough to reach the daily mean.

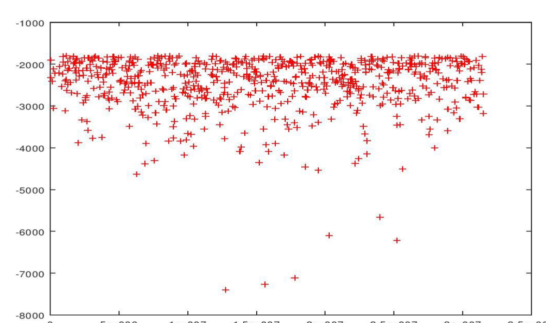

Figure 9. Zero series longer then 30 minutes (1800 seconds) along the year. X axis seconds from recording start, Y axis length in negative seconds.

When we perform for the D1 zero series group the same computation done for D2, we get Figure 10.

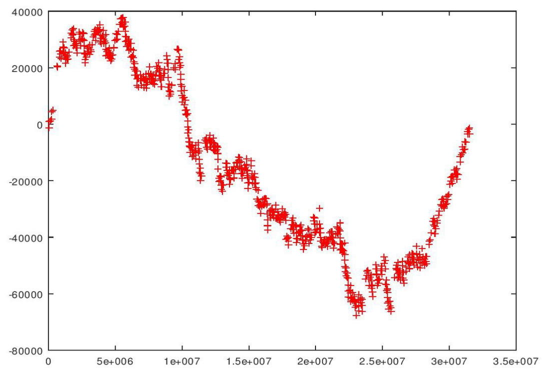

Figure 10. Difference of the D1 Zero Series sum less the sum of the theoretic daily mean along the year. X axis seconds from recording start, Y axis difference in seconds.

It is possible to note a small fluctuation similar to a circannual rhythm with peaks around middle August and middle April. The distance between the August - April peaks is about 80.000 sec (nearly 24 hours). That may seem a large gap, but that would mean that from August to April the mean daily length of D1 series is about 15 minutes longer than the April to August one, a small amount largely inside the day to day variability.

B. *Pulse analysis*

If we compute the basic model in Figure 7, we find that the central part of the short series is delimited by a threshold with daily values ranging from 20 to 40 seconds. That means that zero and non zero series long up to 20 to 40 seconds can freely move among them, but above those values that freedom is lost and longer intervals must be followed by series below that threshold. We may think that lost of freedom as the creation of couples of series, but it could also be that that "bond" is only more visible, i.e., that the “bond” that appears for long series exists, somehow, also for the sequences of short series. If we compute the distribution of couples of zero and non zero series, we find that the most important one is the (-1, 1) that covers 7% of the couples of the year. The couple (-1,+1) means that the accelerometer measures something that is shorter than one second and that is preceded by a pause longer than one second but shorter than 2 seconds. With the MW8 we cannot explore more in details that couple, due to the data processing characteristics explained in Section II. That couple is something that seems a pulse or a beat. We may suspect some kind of artefact, for instance from the heartbeat, but that would not explain the very long zero series, that would be randomly interrupted by an artefact.

The above was suggestive toward the analysis of actigraphic recordings as if those couples of series were “pulses”. We may think of activity driven pulses (+/-) like “contraction and relax” or inactivity driven pulses (-/+) like “charge and discharge” and in the following we will consider the latter.

That “pulse” approach is new for actigraphy and in order to explore an uncharted area, an analogy could help. If we use the electrocardiography (EKG) analogy, then the actigram is like the electrocardiogram and the length of the “actigraphy pulses” (i.e., the length of one zero-series plus the following non zero one) is analogue to the R-R interval (where R is a point corresponding to the peak of the QRS complex of the EKG wave; and R-R is the interval between successive Rs). Figure 5 can then be “read” as the plot of the set of those pulses.

The range of R-R interval is about 200-2000 msec and the one of what we may call Wrist Actigraphy Pulse (WAP) is 2-8000 seconds. Those ranges barely touch each other and therefore R-R and WAP work in two different time scale. That would make those data complementary for the evaluation of lifestyles, and for sleep it has been already done [16].

So, it seems that WAP is a possible way to expand the study of zero and non zero series and that would put actigraphy in the same “basket” of other pulse analysis (HRV, Arterial pressure variability (APV), Oxygen pulse variability [29], etc.).

C. *Percent of zeros*

A more traditional approach, could be counting the zeros inside a defined interval.

1) *One minute.*

For instance, if we take one minute and we count the zeros, for each minute we get a number between 0 (maximal activity) and 60 (total immobility). The plot of the first day of the recording (1440 minutes) would be as in Figure 11.

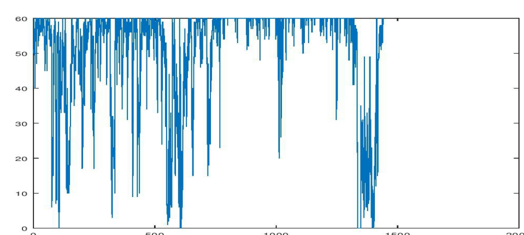

Figure 11. Number of Zeros -Day one Start time 09:52:00. X axis in minutes, Y axis number of zeros in a minute.

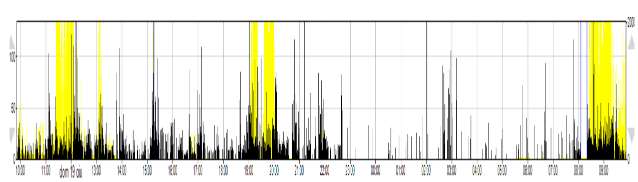

Figure 12. Day one at epochs of one second: Actimetry in Counts (black) with range on the left, light in Lux (yellow) with range on the right. Start time 09:52:00

The software Motionware provides a very similar value named “Immobile time Percent” inside the Assumed Sleep

Time (Table I), but accepting some very short activity [21], while in our case all values must be zero. We can compare Figure 11 with the standard Motionware activity plot in Counts as in Figure 12. With the zeros counting, it is easier to see that also during the day there are several minutes without any movements.

2) Three hours

If we divide the day in eight segments of three hours, we can count the number of zeros inside those intervals and get 8 numbers each day. It is also possible to express that number as a percent, i.e., percent of zeros (POZ) in 3 hours (POZ3h), and plot them in a circular way, instead of against a linear baseline. In that way, we get Figure 13 where the circumference is the year with the value 1 (total immobility) and the centre is the 0 (maximal activity) and there is a dot for each day.

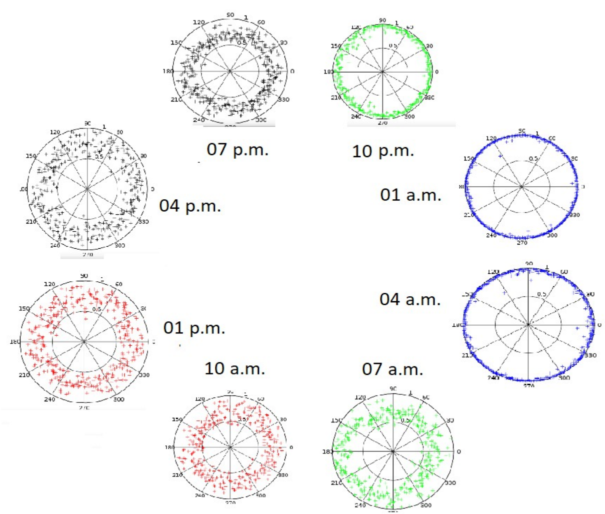

Figure 13. Full year. Zero values percent of 3 hours segments. The time is the start of the 3 hours segment. Circumference is one year, divided in months, 0 is 17 June 2016.

With that type of display, it is possible to see that a percent of zero values lower than 50% (internal circumference) is exceptional and that the circadian behaviour is consistent over the year in all segments.

3) Twelve hours

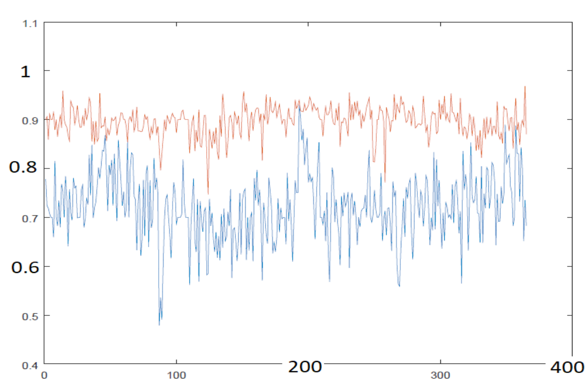

Figure 14. X axis: day of the year - Y axis: zeros percent in the time intervals 10am-11pm (blue) 11pm-10am (red).

If we divide the day in two pieces, like from 10 am to 11. pm and from 11 pm to 10 am, and compute for each day of the year the zero values percent of the two segments we can plot Figure 14. The two segments show a quite different behaviour along the year (few days with more than 5% of n/a data are removed for a better graph display).

The change of the clock to summertime (27 March to 30 October 2016; 26 March to 29 October 2017) may be responsible for some asymmetry in Figures 13 and 14 because solar time is from day 135 to day 285.

4) Segmentation

Motionware software offers the option to compute a 24 hours mean of the activity. If we average 3 months we see the pattern in Figure 15.

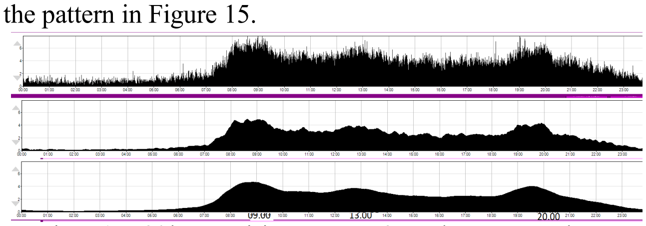

Figure 15 . 24 hours activity mean over 3 months. Upper graph no smooth, then 10 minutes smooth and one hour smooth. Start hour midnight. X axis 24 hours with hour divisions, Y axis Counts

Something similar would it be meaningful for POZ of 1 minute (POZ1)? If we plot the sum of POZ1 of 3 months for segments of 24 hours +/- 6 minutes, the pattern more visually similar to the one of a single day is exactly 24 hours (Figure 16).

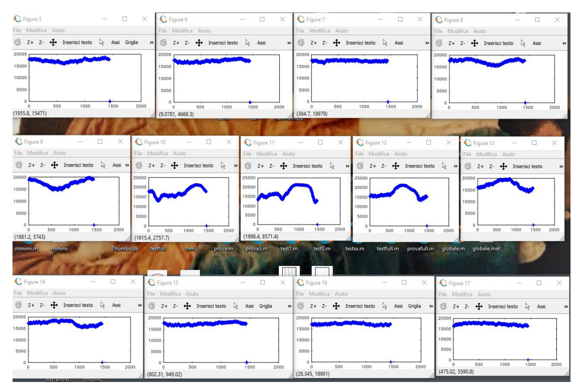

Figure 16. POZ1, 3 months sum of segments from 1434 to 1446 minutes. X axis minutes, Y axis POZ1 sum.

So, it seems that the segmentation of 24 hours is useful. We would get similar results from autocorrelation, but the methodology would require hypothesis on the data structure. The approach used, evaluating some segmentation and selecting the one more similar to the single day profile, is suitable for a machine learning algorithm and does not need hypothesis on the data structure. The development of that algorithm is a task for future work.

For the moment, let us accept the 24 hours segmentation. If we compute the sum of POZ1 on the 24h segmentation, we find that the parameter is sensible enough to show the summer hour shift (Figures 17 and 18).

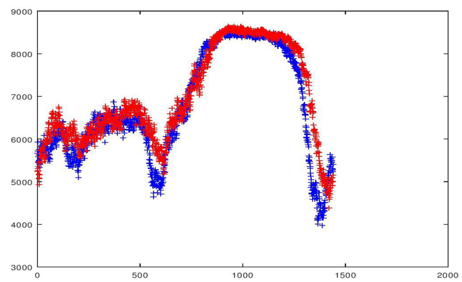

Figure 17. Sum of POZ of 1 minute (POZ1) over 5 months using a 24 hours segmentation (1440 minutes). Y axis POZ1 sum. Summer time 5 months in blue, standard time 5 months in red. Start time 09:52:00

It is possible to note that the profile in Figure 17 has two levels divided by two long transitions and therefore there is a large range of values that split the profile in two separated segments, as demonstrated in Figure 14. In Figure 13, those transitions are in the two segments 10 p.m.-01 a.m. and 07 a.m.-10 a.m.

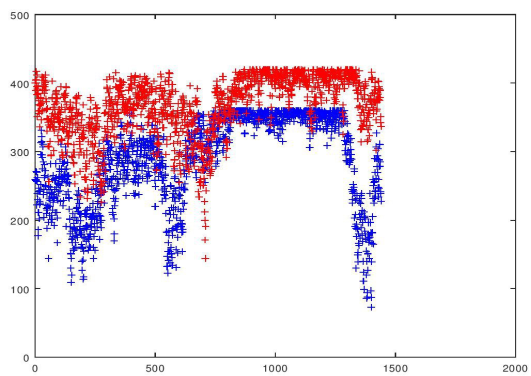

Figure 18. Sum of POZ1 over 1 week using a 24 hours segmentation (1440 minutes). Y axis POZ1 sum. Summer time in blue, standard time in red. Start time 09:52:00

The description of the plotted lifestyle of the subject would be: walk and breakfast (the first peak in Figure 15 and the last in Figure 17), office time, walk and lunch (peak), office time, walk and dinner (peak), after dinner until bedtime. Overall, it seems that the transitions from full wakefulness to deep sleep and back suggested by the activity levels, are long, taking more than one hour each. Those long transitions possibly explain why, in general, several different actigraphy systems and methodologies are able to recognise the wake and sleep circadian levels, because the selection of the threshold does not have to be precise. That will be true as long as the lifestyle pattern is "simple" as in this case and there are no important naps or long awakening at night.

It is worth to note that the use of POZ, like all the percent parameters, moves the scale of the parameter from the very high numerical difference of the Counts as in Figure 12, inside a recording and among recordings, to a fixed scale for all. The price to pay for that advantage is the losing of the information about the relative intensity of the movement. The "automatic" compression from the scale used for POZ1, makes the graph less spiky and usually there is no need for added operations in order to decide where the peaks are. We may then think of Figure 17 as the probability distribution of the movement of the non dominant wrist of the subject's lifestyle.

From co-recordings made after the published year, it seems possible to relate the slow down of activity after dinner with the dip of the core temperature [27]. So, it seems the POZ1 has the potential to become an useful complementary parameter for actimetry data analysis.

V. DISCUSSION

A first step needed in any research is to understand the tools we use. Section II and Section III explain how the Motionwach8 works and why it differs from all other actigraphic system in the market.

Historically, the first objective of wrist actigraphy analysis was to classify sleep and wake states. An epoch of pre selected length (mostly 1 minute or 30 sec) is classified as Wake or Sleep, usually on the base of a threshold value, looking for a procedure that would provide parameters with good correlation to the PSG. The first set of parameters provided by the Motionware software (from "assumed sleep" to "mean wake bout" in Table I) are in that line of work. That evaluation is helpful as long as the time when sleep is expected (for the Motionware software the interval between the marks Light off and Got up) is well defined by external inputs [2].

The second attempt was to evaluate activity and immobility (in the case of Motionware software, the parameters from "Immobile mins" down, in Table I), using procedures more tied to the objective description of the data recorded. Traditionally, the data is analysed as a table of a dependent variable (activity Counts) and an independent one (time) with fitting methods like Cosinor [30]. That approach is quite difficult when 80% of values are zeros and push to focus on the study of those zero values. Over the years, there were studies on zero values, also called "immobility" [31]. It is one area of studies that is getting new attention [32] and the higher granularity of one second epochs has already shown some potential [16]. POZ may become another useful parameter because it is easy to compute and needs a small amount of memory, allowing long recordings for monitoring purposes. It offered already at least one result pointing out the permanent circadian distribution of the percent of zero values, as shown in Figure 13 and Figure 14.

However, the information provided by those analyses are always the same, no matter past, present and future computations and displays: we try to document and describe what a clinician would evaluate simply looking at the raw data in the standard printout of a week long recording i.e., if the daily pattern is regular or not, that there is more activity during the day than during the night (or similar consideration related to the working life), if the night time is without major interruption (Dr. Gioacchino Mennuni, personal communication). That description does not really needs a numerical evaluation, beside research studies.

In order to improve the situation, different approaches are needed. It is often overlooked the basic fact that any analysis method requires a model of the data we want to study. It is important then to underline that all the above historical analysis imply that any sample is considered equivalent to another, no matter when it is recorded, i.e., a movement of x Counts at noon has the same meaning of a movement of x Counts at midnight. And therefore making acceptable to compare the values measured in the two body states.

Sleep has always been related to the idea of "rest", connecting the seen "immobility" during sleep to the "immobility" of the wakefulness. After centuries, Electroencephalography (EEG) demonstrated the mistake showing that the highest level of immobility "REM muscle atonia" is a quite active state of the body. Nevertheless, the idea of sleep as "rest during an ongoing activity", is still entrenched (about someone asleep, we still say "he is resting") also in clinicians and researchers work, with methodologies that try to find something quantitatively less or more present instead of something qualitatively different. With the hypothesis that the series of zeros, not the individual sample, are functionally similar we enter a new area of studies. The epoch recorded has a different meaning depending when it is recorded, in this case, inside or not a series of a defined length.

The exploration of series and their dynamics is, as far as we know, a new area of research for actigraphy analysis. The series analysis demonstrates that, for some parameters, between wake and sleep there is not only a quantitative difference "more of the same immobility", but some qualitative one, with series that are possible only during well defined time frames.

We found that:

- the large part of an actigraphy recording is made out of short series;
- data is skewed, with a larger range for zero series than for non zero series;
- there is a threshold that limits the possible interaction among series based on their length and that divides them in "short" and "long" series;
- long zero series may be divided in groups (like D1, D2, D3);
- some of those groups are concentrated during the night with a circadian pattern constant over the year;
- the longest series of zero values are allowed only during sleep (personal communication).

The length of series seems not to be directly related to sleep stages and co-recording of polygraphic data is needed to explore that relationship.

The analysis of series suggested the idea that the couples of series, not the single series, could be functionally similar. The similarity of the couple of series with a pulse, opens the possibility to apply to the actigraphy data the large panoply of analysis already attempted for other "pulses". For instance, when labelling all non zero samples as "1", we create a binary coding suitable for Symbolic Dynamics. It is then intriguing to see a possible common framework for the analysis of different signals of the activity of the autonomous nervous system.

VI. Conclusion and Future Work

For the first time, we make available one year of wrist actimetry in real life, stored at one seconds epochs. The raw data described in this article are freely available to researchers on the National Sleep Research Resource (NSRR) platform .

Most of the activity values stored by the Motionwatch8 are equal to zero. Examples of ways to study those zeros and to display them are introduced.

The analysis of the published year is still limited:

- the issue of the "second door" of sleep has not been discussed;
- the search for a suitable approach to the study of actigraphy is still open and maybe this work will allow actigraphy to enter the network physiology field [33];
- it is unexplored if the intensity of the movement and the light recorded by the MW8 may add useful information.

The recording of the actigraphy inside the research is today more than three years long and there is a large area for further developments, for instance:

- all the issues related to the correlations with other biological signals are to be explored, starting from the difference between trunk and wrist actigraphy up to the correlations between actigraphy and PSG;
- of special cultural interest, at least for the author, would be to bring actigraphy, electromyography and eyelid closure under the same theoretical motor control framework.

The research described in this article is still a ground breaking type of work that creates more questions than providing answers, but new insights on possible analysis of actigraphic data are already obtained that stimulate to pursue the research. Hopefully, other researchers will look for new tools to analyse human motor activity and clarify the role of actigraphy in the personalised medicine.

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