Monitoring circadian rhythms of night-shift operators with Hidden Markov Models

Poster paper: CSCI-RTHI

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***Abstract*— Chronotherapy refers to the delivery of therapeutic treatments following a person's physiological cycles, also known as circadian rhythms. These cycles may be thought as an individual's "biological clocks", having an approximate periodicity of twenty-four hours. Recent research has found that coordinating with and adapting to circadian rhythms can maximize treatment effectiveness, minimize treatment side effects, or both. However, disturbance of circadian rhythms is not limited to sick patients. For example, sleep perturbation may induce a disruption of circadian rhythms, similar to acute or chronic stress. In the present article, we discuss the interest of gathering information concerning circadian rhythms of night-shift workers and applying Hidden Markov Models to such data in order to extract important information about these rhythms.**

***Keywords*—chronotherapy, stress, circadian rhythms, hidden markov models**

I. Introduction

When a person´s natural circadian rhythms are drastically altered, the body itself undergoes changes which affect physiological, metabolic, digestive and cognitive stability. These disruptions become more evident when patients have a chronic disease, such as cancer [1] or Alzheimer´s disease [2]. Circadian rhythms have a twenty-four-hour periodicity, approximatively. Research has found that delivering therapeutic treatments adapted to the body´s proper "biological clocks" improves treatment efficacy and minimizes its side effects [3].

Studies have demonstrated that actimetry and temperature monitoring enabled physicians to detect disruptions in circadian rhythms. Ali et al. [4] recently implemented an innovative Internet of Things (IoT) platform to remotely monitor patients' health with pancreatic cancer. Aided by Hidden Markov Models, this multidimensional monitoring system uses rest-activity ratio and body temperature as main circadian rhythms [1]. In addition to physiological measures, patients completed the MDASI and the Pittsburg questionnaires on a daily basis [5,6].

Many studies have investigated the consequences of circadian rhythms disturbance in animals [7], but also in persons with type-2 diabetes [8], neurodegenerative diseases [9], digestive inflammatory diseases [10], as well as colorectal, breast, ovarian, lung or kidney cancers. Such studies showed disrupted circadian rhythms in rest-activity, body temperature and cortisol secretions [11]. Moreover, sleep perturbation may induce a disruption of circadian rhythms too [12,13], similar to acute or chronic stress.

The aim of this study, is to gather information concerning circadian rhythms of night-shift workers from electricity distribution companies who are involved in failures management and emergency repairs. Such investigation could shed some light into stress-related disorders, sleep privation and their link to circadian rhythms perturbation, as well as validating another study performed by our team [14].

On-call personnel from such companies often work under stressful conditions, increasing the risk of fatal accidents and technical incidents. For this reason, growing efforts have been made to automate stress detection based on physiological signals, notably using electroencephalography (EEG) and electrocardiography (ECG). In the present perspective study, we emphasize the importance of monitoring circadian rhythms in workers who experience intense stress as well as frequent shifts in their work and life cycles. Notably, we attempt to (1) detect stress correlates and (2) examine biological risks linked to this way of life, by inspecting night-shift worker´s circadian rhythms of body temperature and actimetry. Such measures will be available by using a chest medical device that continuously evaluates a person´s accelerations per minute and their chest temperature, as described in [1], and compare its efficiency to the same measures acquired by OuraRing, which has proven efficient predictions to menstrual cycles [15]. Taken altogether, this will allow us to:

1. Follow circadian rhythms based on temperature and actimetry.
2. Determine to what point these rhythms are disrupted in night-shift workers who undergo stress.
3. Compare the efficiency and possibly finding correlates between the two types of devices.

II. Protocol & Methodology

In order to be able to find out if circadian rhythms are disrupted in on-call personnel, we must first assess the normal fluctuations in temperature and activity during diurnal work-shifts, thus finding a baseline of such rhythms. This baseline information is commonly called *reference week*. The information provided by the reference week is crucial in determining if circadian rhythms are or not altered—at to what extent—under normal working conditions.

In coordination with managers from the electricity distribution company, we envision to acquire reference week data of approximately thirty night-shift workers under diurnal conditions (reference week data) as well as during actual night work. Such workers will be using the OuraRing device while using the chest collecting device as well (Move 3, Movisens, Germany). This will allow us comparing the efficiency of both types of acquisition devices. Having in mind that night shifts in electrical stations usually involve three-night interventions, we would be able to acquire night working data during all night shifts within a month of work.

979-8-3503-2028-2/22/$31.00 ©2022 IEEE
DOI 10.1109/CSCI58124.2022.00351

A. Hidden Markov Models

Hidden Markov Modelling (HMM) assumes that observed time-series data can be modelled by a Markov process with unobserved states [16]. In our case, HMM is specifically applied to each individual´s data to rank the square root of a 5-minute average period-activity data, assuming that they follow a Gaussian emission distribution conditional on three qualitative states: inactive (IA), moderately active (MA), and highly active (HA). Six rest-activity parameters are computed for each 3-day segment with a 24-h sliding window, with values being assigned to the midpoint of the segment.

The parameters described in table section are computed using time-series analysis algorithms based on HMM and spectral analyses of 3-day segments of the time series, with a 6-h to 24-h shift. To calculate period, amplitude, and acrophase of rest-activity and body temperature, accelerations and chest temperature data recorded are extracted for the last 72 hours. Spectrum Resampling (SR) methods are applied to each 3-day segment of hourly averaged data, with a 6-h step [17]. To characterize the circadian rhythms of rest-activity and chest surface temperature, raw activity counts per min and temperature data recorded during 3-day segments are extracted, with a step of 24 h.

B. Tables

Circadian indicator	**Definition**
Median activity out-of-bed	Out-of-bed daily median activity is computed using raw acceleration data recorded from the estimated time of getting up to that of retiring over three consecutive 24h-spans.
Dichotomy index (I<O)	Percentage of activity counts per minute recorded when the subject is In-bed with values lower than the median activity count when the subject is Out-of-bed. I<O can range from 0 % (totally arrhythmic pattern of activity) to 100 % (regular alternation of sustained activity and high-quality rest over the 24 h). I<O exceeds 97.5% for over 90% of the day-working non-cancerous subjects as compared to half of the patients with gastro-intestinal malignancies.
Rhythm index (RI)	RI is also an indicator of the strength or robustness of the circadian rhythm in rest-activity. RI values can range between 0, corresponding to worst rhythmicity and absence of a consistent rest state in the pattern, up to 1, corresponding to best average quality and regularity of the IA state over the 24 h. This indicator ranged from 0.47 to 0.92 in non-cancerous people.
Center of rest time	HMM also provides an estimation of the average center-of-rest time point during the recording period. This indicator ranged from 01:10 to 06:25 in non-cancerous people.
P1-1	P1-1 represents the probability of remaining in the Inactive state when previously in IA. This indicator ranged from 0.93 to 0.99 in non-cancerous people.
R24	The autocorrelation coefficient at 24 h delay (R24) represents the regular global circadian regularity in the activity pattern. Values of r24 range from -1, for antiphase or opposite regularity (rare) to 0, for no regularity, to +1 for complete daily regularity.
Period	The spectral dominant period is computed for each 72-h span in the circadian (20h ≤ period ≤ 28h) or the circa-hemidian (10h ≤ period ≤ 14h) domains with its a 90% Confidence Limits. If the dominant period is outside both circadian or circa-hemidian domains, or if the period estimate is non-significant, no period, amplitude and phase are computed.
Acrophase	After period computation, the corresponding phase, i.e. the timing of the maximum value of the selected dominant period are computed for each 72-h span.

III. Conclusion & Perspectives

The current study will allow us to discover to what extent are HMM applicable while using medical devices other than the Movisens, such as the OuraRing. We hypothesize that with relatively low effort, we will be able to adapt our current HMM algorithms to the data yielded by the OuraRing. Such results have the advantage not only to show how adaptive and reliable these algorithms truly are, but to make sure that patients wear an easier-to-use device that demands less rigorous follow-ups, both by patients and by medical personnel.

Moreover, valuable information could be extracted from such investigations to eventually port our platform, devices, algorithms and analyses to other diseases or troubles such as stress and obesity, not excluding the possibility to use chronotherapy as means of disease prevention as well.

Acknowledgment

Our team has worked in collaboration with the Paris Saclay University, Pr. Francis Lévi, head of the research unit INSERM U935 and a French electricity provider.

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