Time Series Analysis on the Effect of Light Exposure on Sleep Quality

DSC 180 Capstone Report

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I. ABSTRACT

The increase of artificial light exposure through the increased prevalence of technology has an affect on the sleep cycle and circadian rhythm of humans. The goal of this project is to determine how different colors and intensities of light exposure prior to sleep affects the quality of sleep through the classification of time series data.

II. INTRODUCTION

A. Background Information

As the world undergoes technological advancement on an unprecedented scale, artificial light from man-made sources are becoming ever more prevalent. The extent of this anthropogenic increase in artificial light has become a pollutant, with extensive research showing both ecological and medical consequences [1]. This is due to the importance of light from the sun on the survival and function of the majority of organisms and thus ecosystems on earth. These organisms have developed day/night cycles that cause physiological, behavioral, and metabolic changes which optimize function and are essential for survival. Artificial light interferes with these processes due to differences in wavelength, intensity, and timing from that of light with origins from the sun. A study of satellite images done in 2001, showed that artificial light at night (ALAN) affects 18.7% of global land area [1], through which roughly two thirds of the human population and 99% of humans living in the United States and the European Union, “live in areas where the night sky is above the threshold set for polluted status.” [2] The rapid development of technology and thus rapid increase in artificial light within the last two hundred years has undoubtedly had effects on the biological function of organisms around the world.

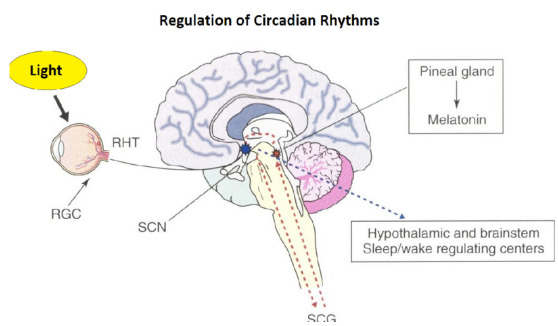
What is most concerning for the health of humans, however, is the ever increasing use of devices with light up displays such as phones, tv’s, and computers for entertainment, work, and communication. Currently, there are an estimated 16 billion mobile devices worldwide [3] with many individuals spending over five hours a day looking at a screen. One biological mechanism that is affected by this increased exposure to artificial light in human beings is the circadian rhythm, through which the body undergoes changes during the night in preparation for sleep and changes during the day in preparation for activity. The circadian rhythm plays major roles in many “physiological processes, such as body temperature, blood pressure, hormone secretion, gene expression, and immune functions” [4], which all have some reliance on diurnal light patterns from the sun and thus the optimized function of these human body processes are impacted by stimulus from artificial sources of light. When light enters the eyes and is picked up by photosensitive ganglion cells, this information is then communicated to the suprachiasmatic nuclei of the hypothalamus, and then to other parts of the brain and body (*fig 1.*). One result is that the brain experiences an increase in

[1] The actual percentage of global land area affected by artificial light is actually smaller due to this data being taken from satellite images and the measure of skyglow.

wakefulness[2] and reduction in homeostatic sleep pressure in the presence of light [5] through the suppression of melatonin, a hormone released by the pineal gland which facilitates sleep and the circadian rhythm.

As a result light exposure during unnatural times can detrimentally affect sleep, which is necessary for human health and function. Sleep deprivation or impairment can lead to many health issues such as impairment to cognition [6], metabolism [7], and immune response [8]. This leads to the focus of this project, which is to determine the effects of light exposure on sleep quality.

fig 1.



B. Data

The data used in this project comes from the Sueño Ancillary study done by The Hispanic Community Health Study / Study of Latinos (HCHS/SOL). The data is composed of wrist-worn actimetry sensor[3] data taken over the course of one week for each participant (n=2252). Measurements are taken from the sensor in thirty second intervals and consist of blue, green, red and white light intensities, locomotor activity, time, and sleep interval indicators [9].

III. METHODS

The outcome variable that we used for the data is sleep efficiency which is defined by the ratio between the duration of time the participant spent sleeping over the duration of time spent in bed for a given night [10].

[2] Wakefulness here is defined as improved auditory reaction time, improved ECG readings indicating alertness, and reduced attentional lapses.

[3] Actiwatch Spectrum, Philips Respironics

The sleep efficiency equation is shown below:

$$SleepEfficiency = \frac{Total\ Sleep\ Time}{Time\ in\ Bed}$$

To calculate this quantity, we isolated the epochs when a subject switches from one activity to another. Thus, the amount of sleep can be calculated by finding the difference between the epochs when a subject sleeps and when they get up from the bed. Similarly, the amount of time spent in the bed can be calculated by finding the difference between the epochs when a subject comes to bed and when they get up from the bed. For a given sleep event x_i, good and bad quality sleep is defined as:

$$\left\{ \begin{array}{l} \text{Good, if } SleepEfficiency(x_i) > 0.95 \\ \text{Bad, if } SleepEfficiency(x_i) \leq 0.95 \end{array} \right\}$$

We created our classifier using the *sktime* library. The classifiers in this library take nested series as feature inputs for univariate classification, and nested series within DataFrames as feature input for multivariate classification. These nested series are indexed and represent the value of the observation that is changing with time, which in our case is the light intensity for white, blue, green and red colors. The target is simply a series of labels of the corresponding feature inputs. In order to get the light exposure time series corresponding to a certain sleep event, we isolated the light exposure until 2 hours before a subject went to sleep. The series for any color of light for different sleep events were then placed within another series, thus creating a nested series. This creates a feature input and target feature that can be used for multivariate time series classification using the *sktime* library. Below is an example of how a DataFrame in this format would be structured:

$$\left[\begin{array}{cccc:cc} L_1^W & L_1^B & L_1^G & L_1^R & SE_1 & SQ_1 \\ L_2^W & L_2^B & L_2^G & L_2^R & SE_2 & SQ_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ L_n^W & L_n^B & L_n^G & L_n^R & SE_n & SQ_n \end{array} \right]$$

The DataFrame is a $n\ x\ 6$ matrix where n is the number of complete active-rest intervals. Each element L series of length 239 (equivalent to 2 hours worth of 30 second epochs) where the superscript represents the associated color of light. SE and SQ represent the sleep efficiency ratio and sleep quality rating respectively.

The first classifier we used is the ROCKET classifier, which is a simple linear classifier based on random convolutional kernels. We used this as our baseline model due to its speed and minimal computational complexity. [11]

IV. RESULTS

V. CONCLUSION

VI. ACKNOWLEDGEMENTS

We would like to acknowledge Professor Benjamin Smarr for his guidance on this project.

The Hispanic Community Health Study/Study of Latinos (HCHS/SOL) was performed as a collaborative study supported by contracts from the NHLBI to the University of North Carolina (N01-HC65233), University of Miami (N01-HC65234), Albert Einstein College of Medicine (N01-HC65235), Northwestern University (N01-HC65236), and San Diego State University (N01-HC65237) (AG05407, AR35582, AG05394, AR35584, AR35583, AG08415). The National Sleep Research Resource was supported by the National Heart, Lung, and Blood Institute (R24 HL114473, 75N92019R002).

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