

DATA ANALYTICS & MACHINE LEARNING

PREMANANDA INDIC, PH.D.

DEPARTMENT OF ELECTRICAL ENGINEERING



ORS Research Design & Data Analysis Lab Office of Research and Scholarship

WORKSHOP SCHEDULE

- >WEEK1: DATA ANALYTICS
- >WEEK2: FEATURE EXTRACTION
- >WEEK3: MACHINE LEARNING



ANALYSIS PLATFORM



University of Texas at Tyler

Get Software Learn MATLAB Teach with MATLAB What's New

MATLAB Access for Everyone at

University of Texas at Tyler

https://www.mathworks.com/academia/tah-portal/university-of-texas-at-tyler-1108545.html

HYPOTHESIS

Scientific hypothesis, an idea that proposes a tentative explanation about a phenomenon or a narrow set of phenomena observed in the natural world. The two primary features of a scientific hypothesis are falsifiability and testability

Source: https://www.britannica.com/science/scientific-hypothesis

>Feature extraction is the process of converting raw data into useful information for machine learning algorithms to predict or classify



>Avoid too many features (computational resources and overfitting)



Statistical Features

(Mean, Standard Deviation, Mode, Skewness, Kurtosis)



 $\mu \rightarrow Mean$ (Mode and Median)

 $\sigma \rightarrow Standard Deviation$

https://sphweb.bumc.bu.edu/otlt/MPH-Modules/PH717-QuantCore/PH717-Module6-RandomError/PH717-Module6-RandomError5.html

Check whether the given two data sets have same features



Check whether the given two data sets have same features







Respiratory Muscles











Bloch-Salisbury E, Indic P, Bednarek F, and Paydarfar D, J Appl Physiol., 2009, 107: 1017-1027



Gee AH, Barbieri R, Paydarfar D, Indic P. IEEE EMBC Conf. 2015, 5855-5858

BIOMEDICAL DATA

LINEAR VS NONLINEAR

>DETERMINISTIC VS STOCHASTIC

>STATIONARY VS NONSTATIONARY

Biomedical data are nonlinear, nonstationary and deterministic / stochastic in nature

Analytical tools are applicable only for linear, deterministic/stochastic and stationary

Sliding Window Method: A few number of files and only one channel



Sliding Window Method: A few number of files and only one channel





Sliding Window Method: A few number of files and multiple channels in each file



Sliding Window Method: Several number of files in a folder

PREPROCESSING

>IDENTIFY OUTLIERS

➢IDENTIFY NOISE



Statistical Features

(Mean, Standard Deviation, Mode, Skewness, Kurtosis)

>Spectral Features (linear)

(Frequency (Rate), Amplitude, Phase, Coherence, Spectrum Entropy)

>Nonlinear Features

(Detrended Fluctuation Coefficient, Multiscale Entropy, Mutual Information)

Statistical Features

(Mean, Standard Deviation, Mode, Skewness, Kurtosis)

MATLAB functions:

mean, sd, mode, skew, kurt

Works on two dimension arrays

Spectral Features (linear)

(Frequency (Rate), Amplitude, Phase, Coherence, Spectrum Entropy)

Transformation of data in time to a new variable (example: Fourier Transform)





https://commons.wikimedia.org/wiki/File:Simple_harmonic_motion_animation_2.gif

➢Nonlinear Features

(Detrended Fluctuation Coefficient, Multiscale Entropy, Mutual Information)

-Complicated and may be useful

HYPOTHESIS

Scientific hypothesis, an idea that proposes a tentative explanation about a phenomenon or a narrow set of phenomena observed in the natural world. The two primary features of a scientific hypothesis are falsifiability and testability

Whatever features you select, and whatever conclusion you reach, always think, so what ?

Source: https://www.britannica.com/science/scientific-hypothesis

Statistical Models are for inference (Linear Regression, Logistic Regression,.....)

Machine Learning Models are for classification / prediction (Linear Regression, Support Vector Machine.....)



Statistical Models are for inference (Linear Regression, Logistic Regression,.....)

Machine Learning Models are for classification / prediction (Linear Regression, Support Vector Machine.....)

GA = 0.0047*Birth Weight + 21.78



r = 0.69 *p* < 0.05

Physiol Genomics 42: 23-41, 2010. First published March 30, 2010; doi:10.1152/physiolgenomics.00027.2010.

CALL FOR PAPERS: Computational Modeling of Physiological Systems

Identifying physiological origins of baroreflex dysfunction in salt-sensitive hypertension in the Dahl SS rat

Scott M. Bugenhagen, Allen W. Cowley, Jr., and Daniel A. Beard

Department of Physiology, Medical College of Wisconsin, Milwaukee, Wisconsin

Submitted 3 February 2010; accepted in final form 25 March 2010

Bugenhagen SM, Cowley AW Jr, Beard DA. Identifying physiological origins of baroreflex dysfunction in salt-sensitive hypertension in the Dahl SS rat. Physiol Genomics 42: 23-41, 2010. First published March 30, 2010; doi:10.1152/physiolgenomics.00027.2010.—Salt-sensitive hypertension is known to be associated with dysfunction of the baroreflex control system in the Dahl salt-sensitive (SS) rat. However, neither the physiological mechanisms nor the genomic regions underlying the baroreflex dysfunction seen in this rat model are definitively known. Here, we have adopted a mathematical modeling approach to investigate the physiological and genetic origins of baroreflex dysfunction in the Dahl SS rat. We have developed a computational model of the overall baroreflex heart rate control system based on known physiological mechanisms to analyze telemetry-based blood pressure and heart rate data from two genetic strains of rat, the SS and consomic SS.13^{BN}, on low- and high-salt diets. With this approach, physiological parameters are estimated, unmeasured physiological variables related to the baroreflex control system are predicted, and differences in these quantities between the two strains of rat on low- and high-salt diets are detected. Specific findings include: a significant selective impairment in sympathetic gain with high-salt diet in SS rats and a protection from this impairment in SS.13^{BN} rats, elevated sympathetic and parasympathetic offsets with high-salt diet in both strains, and an elevated sympathetic tone with high-salt diet in SS but not SS.13^{BN} rats. In conclusion, we have

left unidentified because of these interactions. Thus, these types of measurements become diminishingly informative with an increased degree of genetic nonlinearity.

It seems, then, that more detailed phenotypic measurements are required to understand the underlying etiology and to make sense of the genetics associated with this complex disease. Of course, this is not always possible; many measurements of interest are either inaccessible or simply not practical to obtain. In addition, many of these measurements are operating-point dependent and are influenced to a high degree by physiologic state. Methods of obtaining these measurements often require invasive techniques that introduce stressors (surgical, pharmacological, etc.) that may themselves alter physiological state and therefore the observed measurements. Thus, differences detected in such experimental measurements may not always indicate differences in underlying physiology but can rather indicate differences in confounding variables related to experimental conditions and/or methods.

Mechanistic mathematical models offer a powerful complement to laboratory measurements (5). By accounting for the

Hypothesis: To test the hypothesis that high and low level of salt contents can identify dysfunction in baroreflex mechanisms to indicate hypertension

Give two different levels of salt, low level (blue), high level (red) to dysfunction rat (SS; n=9) and compare with healthy rat (SSBN13; n=6)



Low Salt 135 Features: 130 Mean Blood Pressure (BP) 125 120 Mean 115 Standard Deviation of BP 110 * 105 100

SS

SSBN13





Is there any predictability ?

Mean Blood Pressure (BP)

Standard Deviation of BP



Project 2: Dehydration Detection

1306

IEEE JOURNAL OF BIOMEDICAL AND HEALTH INFORMATICS, VOL. 21, NO. 5, SEPTEMBER 2017

Salivary Markers for Quantitative Dehydration **Estimation During Physical Exercise**

Matthias Ring, Student Member, IEEE, Clemens Lohmueller, Manfred Rauh, Joachim Mester, and Bjoern M. Eskofier, Member, IEEE

Abstract-Salivary markers have been proposed as noninvasive and easy-to-collect indicators of dehydrations during physical exercise. It has been demonstrated that threshold-based classifications can distinguish dehydrated from euhydrated subjects. However, considerable challenges were reported simultaneously, for example, high intersubject variabilities in these markers. Therefore, we propose a machine-learning approach to handle the

osmolality have been shown to track total body water (TBW) loss during physical exercise [2]. The determination of plasma osmolality, however, involves invasive withdrawing of a blood sample and separation of the plasma compartment [3, Ch. 19].

Therefore, salivary osmolality and other salivary markers have been proposed as noninvasive and easy-to-collect alterna-_____

Project 2: Dehydration Detection

Hypothesis: To test the hypothesis that markers of saliva can detect dehydration

Project 2: Dehydration Detection

Features:

Amylase Chloride Cortisol Cortisone Osmolality Potassium Proteins

Project 3: Oxygen desaturation

ORIGINAL RESEARCH published: 02 August 2017

doi: 10.3389/fphys.2017.00555

frontiers in Physiology

Pattern Analysis of Oxygen Saturation Variability in Healthy Individuals: Entropy of Pulse Oximetry Signals Carries Information about Mean Oxygen Saturation

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UCL Division of Medicine, University College London, London, United Kingdom

Pulse oximetry is routinely used for monitoring patients' oxygen saturation levels with little regard to the variability of this physiological variable. There are few published studies on oxygen saturation variability (OSV), with none describing the variability and its pattern in a healthy adult population. The aim of this study was to characterize the pattern of OSV using several parameters; the regularity (sample entropy analysis), the self-similarity [detrended fluctuation analysis (DFA)] and the complexity [multiscale entropy (MSE) analysis]. Secondly, to determine if there were any changes that occur with age. The study population consisted of 36 individuals. The "young" population consisted of 20 individuals [Mean (± 1 SD) age = 21.0 (± 1.36 years)] and the "old" population consisted of 16 individuals [Mean (± 1 SD) age = 50.0 (± 10.4 years)]. Through DFA analysis, OSV was shown to exhibit fractal-like patterns. The sample entropy revealed

OPEN ACCESS

Damian Keltv-Stephen.

Edited by: Radhakrishnan Nagarajan, University of Kentucky, United States Reviewed by:

Paper 3

Project 3: Oxygen desaturation Smokers vs Non Smokers

Hypothesis: To test the hypothesis features of oxygen desaturation can detect the smokers from non smokers



Features:

Mean Variance Sample Entropy Multiscale entropy

THANK YOU



Mohammed Alenazi, Graduate



Pravitha Ramanand, PhD, Postdoc

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