Chapter 42
Personalized Monitors for Real-Time Detection of Physiological States

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ABSTRACT

The authors introduce an algorithmic framework to process real-time physiological data using nonparametric Bayesian models under the context of developing and testing personalized wellness monitors. A wearable device aggregates signals from various sensors while periodically transmitting the collected data to a backend server, which builds custom user profiles based on inferred hidden Markov states. They discuss how these user profiles can be used in various contexts as proxies for fluctuating physiological states and leveraged for various longitudinal classification tasks. Using data collected in a two-week study hosted at Jaslok Hospital, the authors show how physiological changes induced by different environments with various levels of stress can be quantified by the authors' platform. To minimize the dependence on continuous connectivity with the backend server, they introduce a heuristic to enable real-time state identification using the modest processing capabilities of the wearable device.

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INTRODUCTION

The prevalence of networked physiological sensors and related devices today gives us an unprecedented view into a person's body. Privacy concerns aside, the ability for continuous and remote monitoring gives rise to volumes of data that can be leveraged to improve the quality of life of a user. The traditional medical approach to health monitoring treats the human body as a unified system, but focuses on a snapshot of the human body at some instant while relying on only a coarse medical history. A major strength of wearable devices is their suitability for long-term studies that produce substantial longitudinal data. Using this feature we aim to develop a balanced approach to bio-signal modeling by adapting modern Bayesian data analytical techniques to such a study.

A Bayesian generative model gives a probabilistic description of how a data set was generated given prior beliefs, and such a model is particularly useful for learning hidden variables defining the dynamics in a time series data set. These hidden variables can in turn represent the underlying structure that modulates the observed sensor values. In this paper we use such a model to build a learning platform that can be individually trained for each user and reusable for a variety of learning tasks. As a specific example, a study of the effects of stress on various physiological markers was conducted at Jaslok Hospital in Mumbai over two weeks during Summer 2011, where test subjects used a wearable health monitor during their regular work week at preset hours. Each subject also received relaxation exercise training from a therapist for part of the study, and we will use the learned hidden state variables to examine some possible physiological changes that resulted from this intervention.

Objectives

The primary objective of the current work is to investigate how a generative model can be implemented in a wearable *wellness monitoring system* to make meaningful predictions in real-time. Specifically, we will build physiological profiles derived from hidden variables discovered through Bayesian data analysis, and then evaluate these profiles based on their effectiveness in detecting changes in physiological states. We emphasize the difference between the profiles, which are features extracted from the time series data under the assumption of a hidden variable model, and real physiological states such as stress. A successful profile would indicate a quantifiable connection between the hidden variables and the physiological state. Although workplace stress was the focus of the Jaslok study, it is impractical to collect accurate and objective measurements of stress in real-time. Therefore, as a proxy for physiological states we will use each subject's "current activity" (working/relaxing) to validate the profiles. We will explore the prediction performance based on our platform by showing how the learned physiological profiles can be used to make predictions.

A secondary objective is to mitigate the computational difficulties involved in learning a hidden variable model in real-time. The class of generative models is flexible enough to capture a large variety of dynamics, but it has been unclear how the system can be trained and tested on wearable devices with limited capabilities. We will examine how personalized models can be pre-built from a training sample, then used to detect physiological states in real-time. We will see that the performance of real-time classifiers is comparable to that of offline classifiers, which require constant connectivity with the backend processor.

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