Recognition of Physiological Data for a Motivational Agent

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Abstract

Developments in sophisticated mobile physiological sensors have presented many novel opportunities for monitoring coaching of individuals. In this work, we investigate the ability to utilize physiological data to recognize the state of a user while exercising. We discuss recognition of user state using data such as heart rate, respiration rate, and activity level. We also discuss the development of a motivational agent which utilizes the physiological data to help encourage a user during an exercise routine.

Introduction and Background

The development of affordable wearable physiological sensors has presented novel opportunities, but also computational challenges, for monitoring and coaching of individuals undergoing physical rehabilitation. 1.4 million people in the United States sustain a traumatic brain injury annually (Langlois, Rutland-Brown, and Thomas 2004); as a result, many suffer from emotional and motivational problems that may interfere with their recovery (al Adawi, Powell, and Greenwood 1998). This work focuses on the development of an agent that can TBI recovery by monitoring the performance during exercise. Wearable physiologic sensor data serve as the input to a system that provides motivational feedback.

By considering a variety of intelligent recognition techniques, we hope to utilize on-body physiologic data to classify the state and state change trends into desirable and undesirable and associate those with feedback stimuli. The goal is for the system to sufficiently accurately estimate the likelihood of improved or declining performance on an exercise task, in order to provide appropriate coaching. Specifically, we are working with heart rate, respiratory rate, as well as inertial information, such as acceleration. In this paper, we focus on preliminary work exploring the data collection process and detail upcoming experiments. We demonstrate the impact of music as a motivational tool on the performance of a test subject and utilize the data collected to train an initial classification system.

Previous work has demonstrated the impact of music on the performance of physical activity, including increases in heart rate (Edworthy and Waring 2006; Terry and Karageorghis 2006) and increasing the duration and intensity of exercise(Karageorghis, Jones, and Low 2006) based on the music selection. Early attempts have also created systems that aid the user by controlling the music based on feedback (Wijnalda et al. 2005). Our current pilot work is using pacing of jogging as the experimental domain.

Preliminary Study

We used the Zephyr Bioharness, a device worn on the chest, which records physiological information including heart rate, respiration rate, and skin temperature, as well as movement information through accelerometers. The device records information during the exercise session for postprocessing as well as provides real-time information to a secondary device via Bluetooth.

An initial study was conducted to explore the impact of music on a participant's jogging pace as well as explore the ability to recognize changes in the user's performance given from the Zephyr sensor. In this study, a researcher on the project jogged for four 30-minute sessions while listening to music and wearing the Bioharness. During the exercise session, the music was randomly selected between high beats per minute (bpm), low bpm, and 60-second segments of silence. The participant selected the songs in advance from his MUSIC collection, though the ordering was shuffled by the music player during the session.

We focus here on three of the features recorded by the sensor: activity level (see below), heart rate, and respiration rate. Figure 1 shows these features over the course of a single session of jogging including labels of music associated with certain periods. For clarity, these values are normalized to [0, 1].

The activity level is a function of the accelerometers and is recorded in vector magnitude units (VMUs). It responds immediately to changes in speed by the participant. Faster beat music resulted in a 10% increase in activity level when compared to slower music or no music.

Respiration rate (breaths per minute) and heart rate (breats per minute) both exhibited temporal effects when transitioning between songs. This includes a delay followed by a gradual increase or decrease which could extend beyond the current song. Additionally, there is a contextual element to the heart and respiration rate as the direction of change is in-

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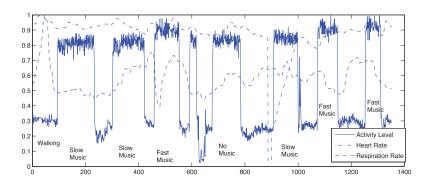


Figure 1: Example data from a 30 minute jogging session

fluenced by the the previous exersion level. In many cases, it was also observed that both of these rates tended to increase significantly after a song when the user slowed to a walk to rest. This corresponded to the user controlling his breathing while jogging but recovering while walking.

We examine the ability to recognize the user's exertion level using the data from the sensor. For this preliminary work, we disregarded the temporal aspect of the data. Additionally, we found that performance with slow music was not significantly different than with no music. Thus, we attempted to recognize two classes: low exertion and high exertion. The data were labelled based on ground truth recorded by the subject. A naive Bayesian classifier was trained on the resulting data. Using a random subset crossvalidation approach, the classifier was able to correctly classify the low exertion points with 81% accuracy and the high exertion points with 87% accuracy, with an overall accuracy of 84%.

Future Work

The study described in this paper represents a preliminary exploratory experiment to examine the capabilities of the sensor in relation to music. The study focused on a singleuser test case.

This preliminary study leads to many improvements to be pursued. One of the most important is to incorporate the temporal component of the data into the analysis and classification. The naive Bayes approach does not capture the temporal component.

Our future work will look into using Hidden Markov Models (HMMs) (Rabiner 1990) for recognition, among other approaches..

The next phase in this work will also expand to collect data from larger groups to account for data diversity and statistical significance. Participants will be asked to jog around a track while listening to selected music. Under this study, music will be selected by the researchers. Data will be record and analyzed in a fashion similar to the preliminary experiment.

A second study will utilize lessons learned from the first study and focus on the development and deployment of a motivational agent for a longer period. Participants will be asked to maintain an exercise routine for several weeks, with and without the aid of the agent. This phase will take advantage of the data for action selection, selecting the correct must based on the current state of the participant.

Finally, although these initial studies center around healthy participants, the insights will act as a baseline for future studies with individuals with traumatic brain injury and other cognitive impairments.

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References

al Adawi, S.; Powell, J.; and Greenwood, R. 1998. Motivational deficits after brain injury: a neuropsychological approach using new assessment techniques. *Neuropsychology* 12(1):115–124.

Edworthy, J., and Waring, H. 2006. The effects of music tempo and loudness level on treadmill exercise. *Ergonomics* 49(15):1597–1610.

Karageorghis, C.; Jones, L.; and Low, D. 2006. Relationship between exercise heart rate and music tempo preference. *Research Quarterly for Exercise and Sport* 77(2):240–250.

Langlois, J.; Rutland-Brown, W.; and Thomas, K. 2004. Traumatic brain injury in the united states: Emergency department visits, hospitalizations, and deaths. Technical report, Centers for Disease Control and Prevention, National Center for Injury Prevention and Control.

Rabiner, L. R. 1990. A tutorial on hidden Markov models and selected applications in speech recognition. In *Readings in Speech Recognition*, 267–296.

Terry, P., and Karageorghis, C. 2006. Psycholophysical effects if music in sport and exercise: an update on theory, research, and application. In *Joint Conference of the Australian Psychological Society and the New Zealand Pscyhological Society*, 415–419.

Wijnalda, G.; Pauws, S.; Vignoli, F.; and Stuckenschmidt, H. 2005. A personalized music system for motivation in sport performance. *IEEE Pervasive Computing* 4(3):26–32.