

Chapter 90

Classification of the Emotional State of a Subject Using Machine Learning Algorithms for RehabRoby

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ABSTRACT

Robot-assisted rehabilitation systems have shown to be helpful in neuromotor rehabilitation because it is possible to deliver interactive and repeatable sensorimotor exercise and monitor the actual performance continuously. Note that it is also essential to distinguish if subject finds the rehabilitation task difficult or easy, since the difficulty level of a task can yield different emotional state, such as excited, bored, over-stressed, etc., at each subject. It is important to adjust the difficulty level of the task to encourage the non-motivated subjects during the therapy. The physiological measurements, which can be obtained from the biofeedback sensors, can be used to estimate the subject's emotional state during the execution of the rehabilitation task. Machine learning methods can be used to classify the emotional state using the features of the biofeedback sensory data. This is explored in this chapter.

INTRODUCTION

This chapter presents primarily the current state of art of the robot-assisted rehabilitation systems, achievements and drawbacks in this area by concluding with challenging research points.

Robot-assisted rehabilitation systems, which have been developed since 1998, have shown to be helpful in neuromotor rehabilitation. Robot-assisted rehabilitation systems deliver interactive and repeatable sensorimotor exercise, and monitor the actual performance continuously. During the rehabilitation process, the task difficulty needs to be decided appropriately challenging to obtain optimal performance from the

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rehabilitation exercise. A rehabilitation task that is too easy or under challenging can be perceived as boring, and an appropriately challenging rehabilitation task can motivate and provide maximum mental engagement for the patients. Mental engagement of patients have shown to be a key factor to improve the outcome of the rehabilitation (Maclean & Pound, 2000). The difficulty level of the rehabilitation task needs to be modified to better suit the patient's abilities. Motor learning theory states that learning rate increases when the rehabilitation task challenges and excites the subjects (Guadagnoli & Lee, 2004).

Nature has been inspiring the technology for modeling and developing better systems for humanity through ages (Habib, 2011), (Banik et al, 2008a), (Banik et al, 2008b). In human-computer interaction, physiological (affective) computing, which monitors, analyzes and replies to human activity in real time using physiological/biological signals, has opened many potential applications in simulated flight, learning, biomedical engineering etc. (Noval et al, 2012). Physiological computing has also been getting quite interesting in rehabilitation robotics area (Koenig et al., 2011a), (Swagnetr and Kaber, 2013), (Badesa et al, 2013). Note that it is important that the robot-assisted rehabilitation system first detect the emotional state of the patient such as boredom, excitedness or overstress from physiological signals during the execution of the rehabilitation task, and then accordingly adapt the difficulty level of this task. Therefore, the patients will not frustrate or overstressed while executing the rehabilitation tasks. (Koenig et al., 2011a).

Various methods such as audio/visual signals, physiological measurements etc. have been proposed to detect the emotion of people (Gunes et al, 2011). Physiological measurements, which are detected using biofeedback sensors such as respiration, skin conductance, temperature, blood volume pulse (BVP), Electrocardiography (ECG), etc., are all information rich sources concerning the physiological responses of the human body. Changes in physiological measurements have previously shown to be used to assess mood and engagement, and to understand emotions of people in a variety of applications (Mandryk & Atkins, 2007); (Rani et al, 2007). Physiological measurements such as heart rate, skin conductance responses, and skin temperature have been used to understand emotions of patients during the execution of a rehabilitation task using a robotic system (Koenig et al., 2011a; Koenig et al., 2011b). Since the raw data from the biofeedback sensors may become inadequate to process, several features from the raw sensor data are defined to classify the emotion states (Koenig et al., 2011a; Koenig et al., 2011b). Note that proper feature selection from the raw sensory data determines the accuracy of the emotional state classification. Machine learning methods (Bishop, 2006) have previously been used to cluster and classify the biofeedback sensory data into the appropriate (or most likely) emotional state (Novak et al, 2012). Additionally, if the emotional state for each sensory data is known, for example through survey results, supervised learning methods has shown to determine the decision boundaries to predict the emotional state for the new sensory data (Novak et al, 2012).

The classification of emotional states based on biofeedback sensor data has been an active research area (See (Novak et al, 2012) and references therein). Clustering the emotional state corresponding to the incoming biofeedback sensor data is an unsupervised learning problem. Labeling the biofeedback sensor data to the emotions of interest is very important for the future supervised learning process, where the rehabilitation task difficulty needs to be adjusted for the incoming sensor data which is not in the training set (Aypar et al, 2014). Besides clustering, two different approaches can be considered separately or jointly to label the biofeedback sensor data. In the first approach, subjects are asked to perform the tasks that clearly differentiate the emotional states of the subjects (watching a funny video, play a video game, doing a boring task) (Koelstra et al, 2012). In the second approach, while the biofeedback sensor data are collected from the subjects during the rehabilitation process, surveys are used so that the subjects

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