# Automatic estimation of cognitive load during robot-assisted gait training

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## Introduction

Robot-assisted gait rehabilitation is becoming more and more common in patients with neurological impairments. Active patient participation in cognitively challenging training sessions are considered essential for the success of gait rehabilitation [2], although objective assessments of cognitive load are difficult to obtain during training. Questionnaires can be used to assess cognitive load, but only at discrete time points, often after training has ceased. Psychophysiological measurements have previously been used to infer to the psychological state of subjects, as every change in the psychological state has a physiological response [1]. Our objective was to determine if measurable physiological responses could be used to provide a continuous estimate of a subject's cognitive load during robot-assisted gait training. We provided subjects with a virtual task during robot-assisted gait therapy to induce different levels of cognitive load. Physiological measurements in combination with machine learning techniques were used to objectively quantify the current cognitive load of the subject performing the task in the virtual environment.

## Methods

### *Hardware and sensors*

The experimental setup consisted of three parts: a commercial gait robot commonly used in gait rehabilitation, the virtual reality display system and the measurement system for physiological signals (Fig. 1). The driven gait orthosis (DGO) (Lokomat - Hocoma Inc., www.hocoma.com) was used for the locomotion training. We recorded heart rate, breathing frequency, skin conductance and skin temperature from subjects walking in the Lokomat. From these signals, we extracted heart rate variability (time and frequency domain), skin conductance responses, the derivative of the skin resistance, and the derivative of skin temperature. The signals were amplified with the g.USBamp of Guger Technologies, Graz, Austria (www.gtec.at). Signals were sampled at 512 Hz according to the recommendations of Malik [3]. All signal processing software was written in Matlab 2008b (The Mathworks, Natick, MA, USA, www.mathworks.com).

### *Virtual task*

A virtual reality task with adjustable difficulty level was used to modulate cognitive load and effort during training sessions. In the virtual task, subjects had to collect and avoid objects which were placed on a straight line and disappeared slowly in front of them. The walking speed in the scenario was controlled via subject's voluntary effort in the DGO. An increase/decrease in effort lead to an increase/decrease in virtual walking speed. In addition to the objects, subjects had to answer questions during the task, which were displayed in a box on the screen. If the statement was correct (e.g. 1+1=2), subjects had to collect the box before it disappeared. If the statement was false (e.g. 1+1=3) subjects had to avoid it by decreasing the walking speed until the box disappeared.

Three different levels of cognitive load were induced by adjusting the difficulty of the task such that the subjects could reach a desired task success. Difficulty was modulated by question difficulty and distance between objects. In the under-challenging condition, task was adjusted such that the subjects succeeded in over 90% of cases. The questions were very simple, the objects were placed far away and disappeared slowly such that subjects had a long time to think about the answer. In the challenging condition, question difficulty and the required reaction time were adjusted so that the success rate was between 40-70%. In the over-challenging condition, subjects had very little time to answer very difficult questions with an average success rate of maximal 20%.

### *Experimental setup*

We performed experiments in eight healthy subjects (29y $\pm$ 6, 5f and 3m, 172cm $\pm$ 8). All subjects gave informed

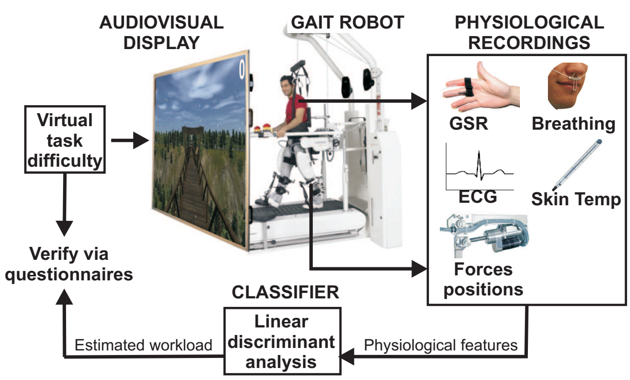


**Fig. 1:** Experimental setup

consent. Subjects were fixed into the DGO with a harness around the hip and cuffs around the legs and walked 2km/h. For safety reasons, all subjects were connected to a body weight support system.

Cognitive load (question difficulty) and physical effort (required walking speed in the VR) were co-varied in our main protocol. Developing an algorithm that estimated only cognitive load required us to also collect data in which these two variables were uncorrelated. This was done by initiating each experimental session with a 6 minute walking period in which physical effort was varied, but no cognitive task was present. During this initial period, subjects completed three different walking behaviors: a) passive, such that the robot provided most of the physical effort, b) in their normal gait pattern, and c) active, thereby overemphasizing the gait pattern and expending additional energy. This initial period was followed by 5 minutes of exercise time, during which subjects could get acquainted with the addition of the virtual task. Meanwhile, the experimenter determined the levels of cognitive load by adjusting the distance between objects and the question difficulty level such that the task success for each condition was reached as described above. Then, the three different cognitive load conditions were presented in randomized order, each 2.5 minutes long.

After each condition of physical and cognitive load, subjects answered questionnaires rate their perceived level of physical and cognitive effort. We used a five-point scale with 1 being the easiest and 5 the most difficult.

### *Automatic classification of cognitive load*

We extracted features from the physiological data as described above, downsampled the data to 1Hz and trained a linear discriminant analysis (LDA) classifier [4]. In addition to the 9 signals extracted from physiological recordings as described above, we also used forces from the DGO and task success data from the virtual task as input to the classifier

We investigated how well the classifier could generalize across subjects by training the classifier on all but the i-th subject and performing classification on the i-th subject, commonly also called "leave one out" classification. All data recorded in the 'no task' condition, regardless of the level of physical effort, was labeled as baseline to the classifier. This ensured that the classifier estimated only cognitive load and not physical effort. To quantify our results, we computed $R^2$, the coefficient of determination between the estimated and the actual cognitive load.

## Results and Discussion

We successfully performed automatic classification of the cognitive load of subjects during virtual reality augmented robot-assisted gait training. We found that the physical effort induced by walking should explicitly be taken into account during classifier training. The most important physiological markers for cognitive load were (in descending order): changes in skin temperature, heart rate variability (time and frequency domain), galvanic skin response and breathing frequency.

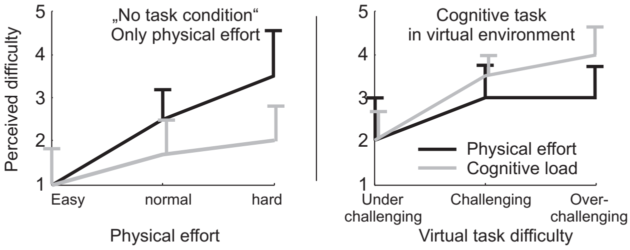


**Fig. 2:** Mean and std values from questionnaires

Perceived physical effort increased with increasing walking activity during the "no task"condition. Same was true for increasing difficulty level of the virtual task. However, perceived cognitive difficulty level increased twice as much during the virtual task conditions compared to the "no task" condition (Fig. 2). We therefore consider cognitive load to be dissociated from physical effort in our task.

The LDA algorithm was able to distinguish three different levels of cognitive load and the baseline. The cross validation achieved in average an $R^2$ value of $0.82 \pm 0.07$ (Tab. 2). The $R^2$ classification dropped to an average of 0.7 when the LDA was trained on a baseline with only one level of physical activity.

**Tab. 1:** Results of the cross-validation classification. Values indicate, what $R^2$ we could reach for correct classificatioon of the three conditions of cognitive load

| Subject | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| $R^2$ | 0.95 | 0.85 | 0.86 | 0.91 | 0.88 | 0.92 | 0.96 | 0.93 |

Our real-time capable approach of automatic classification of cognitive load is the first step towards auto-adaptive, bio-cooperative rehabilitation robots. In the future, we will close the control loop and perform automated control of cognitive load during gait rehabilitation.

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