Decoding Fatigue: Analyzing Offline Handwriting with Machine Learning to Detect Perceived Exhaustion

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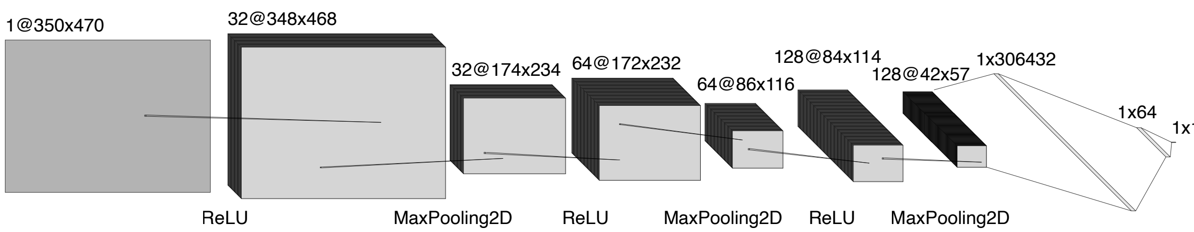

Figure 1: Model architecture of the CNN used to decode exertion.

Abstract

The quality and readability of an individual's handwriting and drawing can be influenced by various factors, including their level of physical exertion. This enables us to explore the quantification of exertion by observing an individual's handwriting. To test this hypothesis, we collected data from 17 participants, building a database of handwriting and drawing samples and their corresponding Borg 10 exertion ratings at the time of drawing. In this paper, we investigate using machine learning techniques to estimate perceived exertion before, during, and after physical activity based on handwriting and drawings. We apply a regression model to compare different drawing tasks and demonstrate that perceived exertion can be predicted using simple line drawings. However, more complex sketches and handwriting demand further research. Our findings suggest that interactive systems could use handwriting and drawing to intervene when users experience excessive discomfort.

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CCS Concepts

• **Human-centered computing** → HCI theory, concepts and models.

Keywords

Exertion, Fatigue, Machine Learning, Drawing, Exhaustion, Discomfort

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1 Introduction and Related Work

During exercise, people perceive sensations from muscles, joints, and the cardiovascular system, contributing to Perceived Exertion [4]. For instance, they may feel the effort, fatigue, muscle aches, and warmth generated by the muscles [3]. Prolonged exertion can also lead to breathlessness, enhancing the sensation of Perceived Exertion [3].

Perceived exertion is assessed through psychophysics, a field studying how physical stimuli from exercise relate to sensory responses and perception [2–4, 9]. Borg, a psychophysicist, defines Perceived Exertion as the overall perception of exertion, including sensations and feelings of effort and stress due to physical work [4]. Robertson and Noble describe it as "the subjective intensity of effort, strain, discomfort, and/or fatigue experienced during exercise" [14]. This sensation can influence the user when interacting with digital systems. For instance, users experiencing exertion might require a more coarse-grained interaction to enable comfortable input.

Past research not only focused on recognizing written content through Optical Character Recognition (OCR)[7, 11, 18] and Handwritten Text Recognition (HTR)[1, 12], but also examined how it relates to biomechanics, focusing on factors like fatigue, pain, and exertion during writing [5, 10], and using handwriting to observe exertion levels [8, 15, 17] through graphology [13, 16]. Garnacho-Castaño et al. explored how handwriting and drawing relate to bodily fatigue after physical activities [8]. They used heuristic signal processing to show that handwriting patterns change with fatigue, even when muscles have recovered from physical exertion, as measured by lactate levels. This suggests that handwriting can be a tool for assessing fatigue and exertion. Recently, Sesa-Nogueras et al. further investigated how fatigue affects handwriting and the accuracy of signature and text-based recognition systems [17]. They found that fatigue negatively impacts signature-based recognition accuracy.

Our paper combines machine learning with handwriting and drawing analysis to quantify perceived exertion, offering new research opportunities. While previous work showed in theory, that handwriting- and drawing-tasks are feasible to quantify perceived exertion, we extend this approach by using machine learning methods. Unlike heuristic approaches, machine learning models can dynamically learn and find patterns unobserved by heuristic approaches. This work forms the ground-laying work to enable exertion detection from simple drawn shapes. The result shows potential and first insights in which properties and designs of drawing- or writing-task enable the detection of insetting exertion. While this approach can be used to automatically quantify exertion, it could also help to detect early motor skill decline in conditions like Parkinson's or arthritis.

2 Data Collection

We first conducted a data-gathering study to enable the investigation using a machine learning approach to quantify perceived exertion. We recruited 17 participants from local gyms who participated in various sports. Each participant received a booklet with detailed instructions and information about the study. They were asked to fill out the survey, as seen in Figure 2, four times during their training sessions when experiencing different perceived exertion levels. Participants were asked to complete the first survey before starting the training session to include recordings with low to no perceived exertion. Finally, participants were also instructed to complete the writing tasks seated, on an even surface, using a provided pen to standardize the writing process.

The survey included three handwriting tasks and a self-rating of perceived exertion based on the BORG scale [4]. The handwriting tasks were as follows: (1) write the English word "jelly," (2) draw

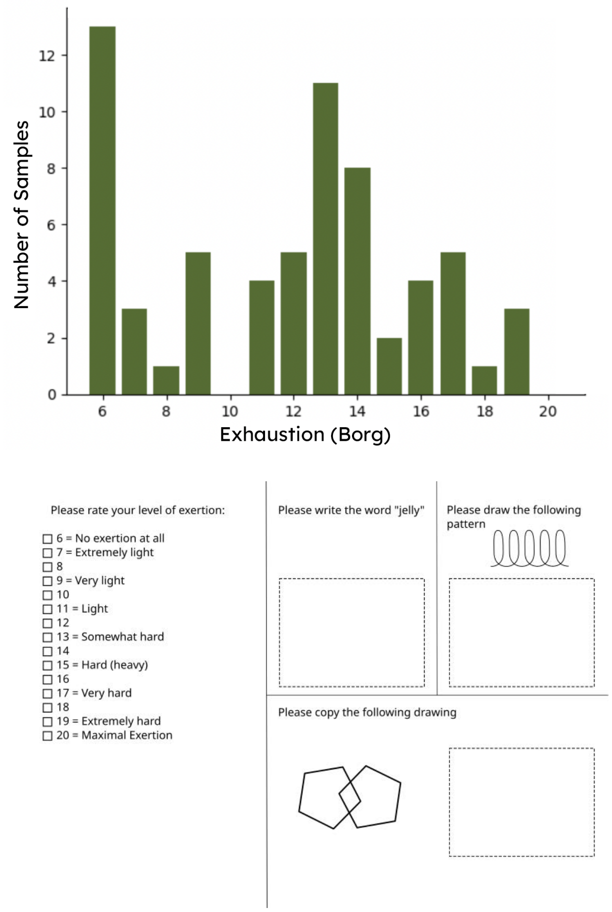

Figure 2: Upper: Number of samples per Borg exhaustion rating. Lower: Writing- and drawing-tasks used to make perceived exertion quantifiable.

a spiral resembling five consecutive loops, and (3) draw two overlapping pentagons. The first two tasks were adapted from Dalia Cilia et al. [6], whose research suggests these tasks may improve classification accuracy in offline handwriting analysis. Task (1) involves copying a common English word with a mix of ascending and descending strokes, while task (2) tests fine motor control with a repetitive pattern, combining elements from Cilia et al. [6] and Garnacho-Castaño, Faundez-Zanuy, and Lopez-Xarbau [8]. The third task, adapted from Garnacho-Castaño, Faundez-Zanuy, and Lopez-Xarbau [8], is a graphical task aimed at assessing cognitive effort. Their work highlighted significant features for "Cognitive Effort" and "Fine Motor Control" tasks through experiments. When exerted, participants showed reduced fine motor control and cognitive effort capabilities, rendering it a very promising candidate for a drawing task.

3 Data Processing

In the following, we evaluated the classification efficiency of using handwriting for detecting fatigue.

Drawing Task	MSE	MAE	R^2 Score
Jelly	8.93	2.22	.36
Spring	7.18	1.84	.61
Pentagons	**4.75**	**1.60**	**.65**
All	11.01	2.40	.37

Table 1: Results of the CNN regression. Pentagons resulted in the lowest error and highest R^2 Score.

3.1 Preprocessing

We scanned the drawing using a scanner (72 dpi). Then, we transformed the scanned drawing into grayscale pictures and rescaled them to the same dimension (350 *times* 470 pixels). The images were then saved with an ID and the exhaustion rating as the file name.

3.2 CNN Regression Analysis, Discussion & Future Work

We trained a CNN, including 2D convolutional layers, max-pooling layers, and dense layers with ReLU activation functions for processing the 2D image data, see Figure 1. To promote model generalization, we employed cross-validation during training. The images were grouped based on the specific tasks they represented. After initial training on the separate task datasets yielded suboptimal results, we implemented a continuous learning approach by training the model twice. We incorporated early stopping and monitoring of the validation set loss. This approach reduces the likeliness of overfitting. We evaluated the performance using three metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), and the R-squared (R^2) score. MSE and MAE provide insights into the prediction error magnitude, while a significant discrepancy between MSE and the square of MAE may indicate the presence of outliers. The R^2 score, ranging from 0 to 1, assesses how well the model explains data variability, with scores above .7 indicating strong performance. The model was trained four times: once for each task and once on the combined dataset containing all tasks.

Table 1 summarizes the results of the regression. Drawing pentagons resulted in the lowest MSE and MAE while showing the highest R^2 score. This task requires both cognitive effort and precise fine motor control to do right. When exerted, both capabilities are declined compared to a rested state. For the purpose of this study, the small sample size was already enough to show the potential of predicting a user's exertion using drawing tasks and which test shows promising results for further investigation.

In future work, we'll adapt the drawing and writing tasks for digital devices like smartphones and explore using everyday input data to measure perceived exertion. In this study, we used the subjective Borg scale to assess exertion, testing non-invasively if drawing tasks can detect it as an alternative to blood lactate measurements. Starting with non-invasive methods is ethically advantageous because it minimizes participant discomfort and risk. This proof-of-concept study thus lays the groundwork for potentially using these tasks to measure metrics like lactate levels or fine motor skills.

4 Conclusion

This paper investigated the prediction performance of perceived exertion through handwriting and hand drawing. We explored this possibility by asking participants to write words and draw figures, which were subsequently used to train a convolutional neural network (CNN) for predicting exertion using regression analysis. Our results show promising results for simple figures, such as line drawings (e.g., pentagons), but less accuracy for more complex drawings and handwriting. Our results suggest that offline handwriting could predict a person's perceived exertion, provided the appropriate writing tasks and suitable machine learning models are used. However, further advancements and research are required, such as gathering additional data, experimenting with various machine learning models, or exploring different writing- and drawing-tasks.

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