Decoupling Cognitive Workload and Physical Motion Effects on Heart Rate Variability Using a Wearable Magnetocardiography Sensor

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***Abstract*—We have recently demonstrated a wearable MagnetoCardioGraphy (MCG) sensor capable of classifying high vs. low cognitive work, i.e., the amount of mental effort a person is exerting when performing a task during a given period of time. However, a major limitation of our previous work was the requirement to eliminate any type of motion for the participants. Here, we explore the effect of motion by employing three (3) different experimental setups, each with a different amount of physical motion and cognitive load exerted. To better understand the effect of motion, an inertial measurement unit (IMU) and a breathing rate sensor are employed in addition to the MCG sensor. Our results show that heart rate variability (HRV), demonstrated through the mean difference in duration between consecutive heartbeats, is at its highest when neither cognitive workload nor motion are exerted. HRV drops when the subject involves cognitive workload and motion. Our results pave the way for additional research in the field, with an utmost goal of catering to specific clinical applications.**

***Index Terms*—Cognitive Workload (CW),Heart Rate Variability (HRV), Magnetocardiography (MCG), Physical Motion**

I. Introduction

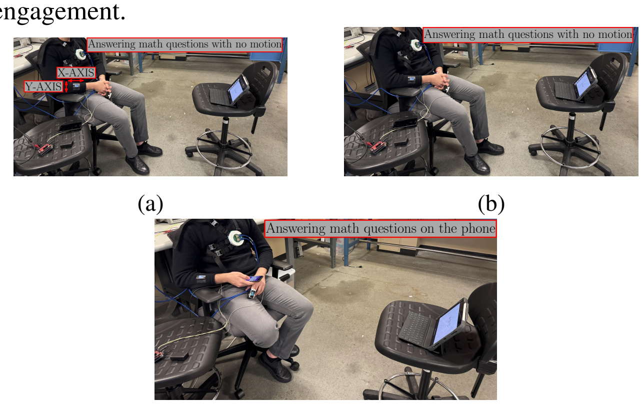
Heart Rate Variability (HRV) provides insights onto the variation in time between consecutive heartbeats [1]. Recent evidence has shown the ability of HRV to classify/quantify cognitive workload (CW), i.e., the amount of mental effort a person is exerting while performing a certain task during a given period of time [2] [3]. This is particularly promising as previous methods of quantifying CW (such as ElectroEncephaloGraphy (EEG) or pupillometry) are complicated to build and operate, and not viable in day-to-day natural environments.

Indeed, we have recently reported a portable MagnetoCardioGraphy (MCG) sensor for capturing HRV in a non-contact manner that was demonstrated to be sensitive to CW [4]. The operating principle of the sensor is based on Faraday's law, which states that the voltage induced on a coil from a time-varying magnetic field is:

$$V = AN\frac{dB(t)}{dt}. \tag{1}$$

However, a major limitation of this previous work was that participants were requested to remain completely motionless. Distinguishing changes in HRV caused by cognitive exertion as opposed to physical exertion remains a challenge.

In a major leap forward, we herewith propose an experimental setup that differentiates changes in HRV caused by physical vs. cognitive exertion. Our approach is based on having a subject perform different tasks, with different levels of physical motion and cognitive workload exerted in each, along with sensors placed on the body to validate whether the variations in HRV are the result of motion or cognitive engagement.



(a) (b) (c)

Fig. 1: Visual for (a) sitting without any motion, (b) answering math questions mentally without any motion, and (c) answering math questions on a phone.

II. Experimental Setup

A proof-of-concept experiment was performed with a goal to demonstrate the ability to differentiate changes in HRV caused by physical vs. cognitive activities. One male adult participant was recruited and equipped with an Inertial Measurement Unit (IMU) and a breathing rate sensor. The IMU, placed on the participant's right hand, was used to show acceleration in the x, y, and z directions. The MCG device used is the same as the one discussed in [5]. To validate the MCG results, an off-the-shelf 3-lead ECG sensor was also employed. Multiple recordings with different setups were performed for a duration of 5 minutes each. During each recording, all sensors were collecting data simultaneously.

Three setups were tested, as shown in Fig. 1. The first setup comprised of the subject sitting still on a chair. In the second setup, the subject was asked to mentally verify pre-solved math problems, some of which contained incorrect answers. The task was to evaluate each question mentally and indicate whether the presented answer was true or false, while refraining from verbal responses or physical movements. A total of 90 two-digit addition and subtraction equations were

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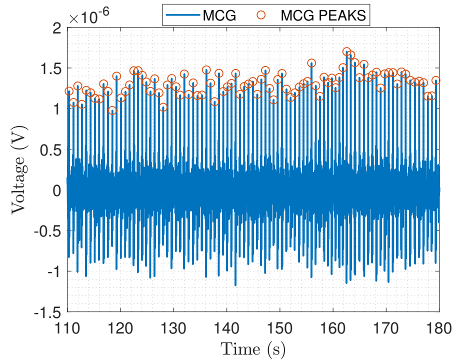
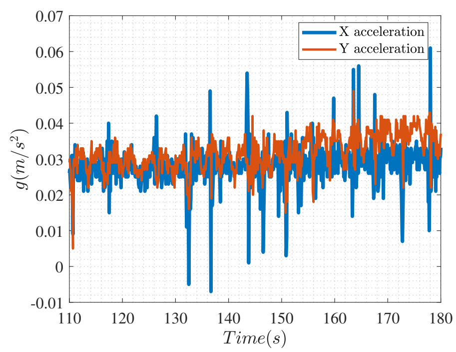


(a)



(b)

Fig. 2: Zoom-in on (a) MCG data obtained from the subject while answering math questions on the phone and (b) IMU data of the same experiment.

displayed and the subject had 5 seconds for each. For the third setup, the subject answered the same math questions while recording the answers (True or False) on a phone. The participant was requested to sit throughout the full experiment as the results are expected to change with posture [6].

III. Results

Fig. 2 shows a zoom-in on (a) the MCG data obtained from the subject while answering math questions on the phone and (b) gravitational acceleration "$g(m/s^2)$" obtained through an IMU for the same experiment. To detect the heartbeats in the recorded MCG signal, we used the algorithm demonstrated in [7] [8]. The peaks detected in Fig. 2a were then used to calculate the HRV, herewith defined as the mean in the difference in duration between consecutive heartbeats. Fig. 2b indicates that the subject was moving in the X and Y directions, where the reference axis is shown in Fig. 1a. These measurements are used to validated our hypothesis that HRV will drop further when motion is involved.

Table I summarizes the results obtained and setups. Specifically, after processing the raw data, the experimental setup where the subject was sitting without any motion resulted in the highest HRV value of 840 ms. The HRV value dropped to 821 ms when the subject was mentally answering math questions. The lowest HRV value of 798 ms was recorded when the subject used a phone to answer the math questions.

These results align with our theoretical hypothesis. According to [4] [8], HRV is expected to drop when motion and/or

TABLE I: Summary of Experimental Setups

Activity	Motion	Cognitive Load	HRV (ms)
Sitting Still	No	No	840
Mentally Answering Math Questions	No	Yes	821
Answering Math Questions on Phone	Yes	Yes	798

CW are involved. Thus, sitting without involving any type of motion is expected to yield the highest HRV as it involves minimal to no motion and cognitive workload. Conversely, the lowest HRV is expected when the subject is answering math questions on the phone, as this involves both motion and cognitive workload.

IV. Conclusion

In this work, we demonstrated the ability to decouple changes in HRV from physical and cognitive exertion, as collected via a portable MCG sensor. To do so, we created three experimental setups, each with a different level of physical motion and cognitive workload involved. Our results demonstrate that changes in HRV can be tracked and assigned to motion, cognitive workload, or both. This outcome is very crucial for CW quantification as it is essential to identify the amount of mental effort exerted by a subject when performing a task while eliminating the aspect of motion.

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