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A System to Monitor Cognitive Workload in Naturalistic, High-Motion Environments

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Abstract. Across many careers, individuals face alternating periods of high and low attention and cognitive workload can impair cognitive function and undermine job performance. We have designed and are developing an unobtrusive system to Monitor, Extract, and Decode Indicators of Cognitive Workload (MEDIC) in naturalistic, high-motion environments. MEDIC is designed to warn individuals, teammates, or supervisors when steps should be taken to augment cognitive readiness. We first designed and manufactured a forehead sensor device that includes a custom fNIRS sensor and a three-axis accelerometer designed to be mounted on the inside of a baseball cap or headband, or standard issue gear such as a helmet or surgeon's cap. Because the conditions under which MEDIC is designed to operate are more strenuous than typical research efforts assessing cognitive workload, motion artifacts in our data were a persistent issue. Results show wavelet-based filtering improved data quality to salvage data from even the highest-motion conditions. MARA spline motion correction did not further improve data quality. Our testing shows that each of the methods is extremely effective in reducing the effects of motion transients present in the data. In combination, they are able to almost completely remove the transients in the signal while preserving cardiac and low frequency information in the signal which was previously unrecoverable. This has substantially improved the stability of the physiological measures produced by the sensors in high noise conditions.

1 Introduction

Across many careers, individuals face alternating periods of high and low attention and cognitive workload, which can result in impaired cognitive functioning and can be detrimental to job performance. For example, some professions (e.g., first-responders, doctors and nurses working in an emergency room, pilots) require long periods of low workload (boredom), followed by sudden, high-tempo operations during which they may be required to respond to an emergency and perform at peak cognitive levels. Conversely, other professions (e.g., air traffic controllers, market investors in financial industries, analysts) require long periods of high workload and multitasking during which added tasks may result in cognitive overload which can lead to mistakes. It is relatively simple to assess cognitive workload using neurophysiological sensors (e.g., functional near-infrared spectroscopy; fNIRS) when individuals are seated. When cognitive workload increases, there is a corresponding increase in prefrontal blood flow that correlates with increased task engagement. Once the task becomes too difficult, there is a decrease in blood flow that correlates with disengagement from the task and decreased performance [1-4]. However, methods to assess cognitive workload during normal activities are only recently emerging [5; 6]. Even in these studies, "motion" includes nothing more strenuous than walking [7]. To address this gap, we have designed and are building an unobtrusive system to Monitor, Extract, and Decode Indicators of Cognitive Workload (MEDIC) in realistic, sometimes high-motion environments. Such a system could warn individuals, teammates, or supervisors when steps should be taken to augment cognitive readiness.

2 Method

We first designed a forehead sensor device that includes a custom fNIRS sensor and a three-axis accelerometer designed to be integrated into a baseball cap or headband, or standard issue gear such as a helmet or surgeon's cap. This sensor is more portable and less obtrusive than most commercially-available sensors. Fig. 1 shows our fNIRS sensor device sensor alone (top left), mounted inside a helmet (top right), being worn during a jump roping task (bottom left), and being worn during a medical training simulation (bottom right).

Fig. 1. Custom fNIRS sensor alone (top left), mounted inside a helmet (top right), worn during jump roping (bottom left), and worn during a medical training simulation (bottom right)

The first full evaluation of this sensor suite included nineteen teams of three undergraduates completing physical and cognitive challenges including: (1) baseline (sitting quietly); (2) word list memorization; (3) balance board; (4) 20 questions; (5) puzzle; (6) hot potato; (7) logic problems; (8) moving boxes; (9) word list recall; and (10) team jump rope. We chose these tasks because the effect on physical and cognitive workload is well validated in the literature, giving us the ability to predict the cognitive and physical workload that should result. A subset of tasks increase only cognitive workload (e.g., word list memorization, 20 questions), a subset of tasks increase only physical workload (e.g., moving boxes), and a subset of tasks increase both cognitive and physical workload (e.g., balance board). In this way, we can evaluate the ability of MEDIC to accurately model changes in cognitive workload during physical activity.

Word list memorization requires the team to remember as many words as possible, either as individuals or as a group. The limits of individual short-term memory are widely documented starting with Braine [8]. At the team level, the concept of transactive memory refers to remembering what is distributed across team members [9]. Balance board requires the team members coordinate rolling a ball edge to edge on a large, flat, weighted board without dropping it for a specified amount of time. For twenty questions, each team member is assigned an object and they need to ask yes-or-no questions (up to 20) of the experimenter to identify the object. This task has been used at the individual level to examine problem solving across the life span [10]. A variant of twenty questions has been used by Shockley at the team level by having a pair compare cartoon pictures [11]. For the puzzle task, we used standard cardboard or plastic puzzles of varying difficulty, giving teams up to two minutes to cooperate on constructing the puzzle. Various tasks have been used to measure individual spatial cognition such as the mental rotation task [12]. A similar task has been used with school-aged children to test interactions in single-sex and mixed-sex dyads during interactions involving Science Technology Engineering and Mathematics (STEM) learning [13]. For hot potato, team members must each maintain balance on a BOSU ball while passing weighted (medicine) balls from one team member to the next. Successful teams will coordinate their timing to maintain stability during the throw and catch while completing the circuit as quickly as possible. Increased postural sway of individual team members being correlated with better team performance has been well-documented across a range of conditions in the motor-coordination literature [11; 14; 15]. For logic problems, individuals were given logic problems (e.g., http://www.brainbashers.com/logic.asp). Clues were given in pieces, and teams were allowed to use a large poster board and markers to cooperate to solve the problems. Individual reasoning has been studied by Braine and colleagues [16], and at the team level, research has tied team-based learning to improved critical thinking [17]. For moving boxes, teams must split into dyads to lift and move boxes of variable weights and sizes to construct a wall. Dyads must coordinate with each other to take turns. The size weight illusion—the perception that larger objects are perceived to be lighter than smaller objects of the same mass—is persistent across both individual and team lifting situations. Boxes that are especially large or wide might be incorrectly perceived as light enough to carry safely [18-20]. For team jump rope, team members must jump synchronously to complete a specified number of consecutive jumps. They must coordinate both positioning and jump speed to correctly complete the task. Similar tasks have been used previously to study team coordination [21].

3 Result

Because these conditions are more strenuous than most research assessing cognitive workload, motion artifacts in our data were larger than normal. All wearable NIRS sensors are susceptible to artifacts arising from subject motion; as the subject moves, the sensor can lose contact with the skin or shift position, leading to large transients in the optical transmission, or even baseline shifts. In a typical setting, this is a non-issue because participants or clinical patients are relatively motionless. This is especially problematic when subjects are free to move naturally. These transient or step discontinuities cannot be effectively removed with conventional linear filters – the broad frequency content of the transients mean the signal is not significantly attenuated regardless of the selected frequency range. Moreover, linear filters tend to "ring" in response to transients, leading to contamination of the signal over a wide time period. We therefore have turned to nonlinear methods to remove motion related artifacts. Two of the most effective methods for motion artifact removal in NIRS signals are wavelet transient removal filters applied to the raw optical time course [22] and [23] movement artifact removal algorithm (MARA), which is based on moving standard deviation and spline interpolation applied to the calculated hemodynamic time courses.

There has been significant work comparing techniques for rejecting motion artifacts [4; 24; 25], however, within the large transients, the band-pass filtered raw data was of reasonable quality (i.e., the shape of the raw data was preserved). We needed a technique that would allow us to salvage the data during the high motion event rather than excluding it. We evaluated several standard techniques including MARA spline motion correction [23], wavelet-based filtering [22] and combined MARA and wavelet filtering. Wavelet-based filtering improved data quality to allow salvaging data from even the highest-motion conditions. MARA spline motion correction alone did not further improve data quality. Fig. 2 shows the entire time series of data (left) and a zoomed in window of 20 seconds of data (right). The black dashed line in the figures on the left indicate the data included in the 20 second zoom. The left column shows how motion artifacts are removed on the entire series, while the right column shows how artifacts are removed in detail.

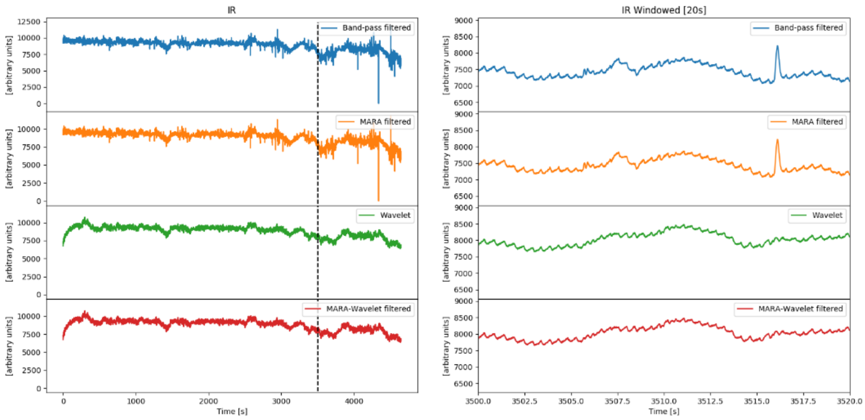

Fig. 2. An entire time series of raw infrared (IR) reflectance data (left) and a zoomed in window of 20 seconds of data (right). The black dashed line in the figures on the left indicate the data included in the 20 second zoom.

4 Conclusion

Our testing shows that each of the methods is extremely effective in reducing the effects of motion transients present in the data. In combination, they are able to almost completely remove the transients in the signal while preserving cardiac and low frequency information in the signal which was previously unrecoverable. This has substantially improved the stability of the physiological measures produced by the sensors in high noise conditions. We are currently analyzing our time-series data to determine whether information on oxygenated blood volume alone is enough to assess cognitive workload as it is with computer-based tasks [1; 3], or whether the effect of physical activity requires the use of additional variables to assess cognitive workload. As we are building up our data processing and modeling pipeline, we are also collecting data for our next evaluation of MEDIC at Vanderbilt Medical School (Nashville, TN, USA) where we will assess medical students, residents, and faculty members during high-fidelity training simulations.

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