EEG Movement Artifact Suppression in Interactive Virtual Reality

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Christoph Tremmel[1], Christian Herff[2], and Dean J. Krusienski[3]

***Abstract*— The integration of electroencephalogram (EEG) sensors into virtual reality (VR) headsets can provide the capability of tracking the user's cognitive state and eventually be used to increase the sense of immersion. Recent developments in wireless, room-scale VR tracking allow users to move freely in the physical and virtual spaces. Such motion can create significant movement artifacts in EEG sensors mounted to the VR headset. This study explores the removal of EEG movement artifacts caused by repetitive, stereotyped movements during an interactive VR task.**

I. INTRODUCTION

As virtual reality (VR) technology continues to gain prominence in commercial, educational, recreational and research applications, there is increasing interest in incorporating physiological sensors in VR devices in order to track the user's physiological and/or cognitive state and eventually increase the sense of immersion. The electroencephalogram (EEG) is one promising sensor modality for this application since current VR headsets provide a logical, convenient, and unobtrusive framework for mounting EEG sensors. Recent developments in wireless, room-scale VR tracking allow users to move freely in the physical and virtual spaces. Such motion, combined with the inertia of the VR headset, can create significant movement artifacts in EEG sensors mounted to the VR headset.

Often in interactive VR applications there are a limited set of expected physical movements used to interact in the virtual environment, thus resulting in movements that can be stereotyped. By using the gyroscope and tracking data available in modern VR headsets and hand controllers, it is possible to model and suppress the artifacts created by stereotyped movements, similar to what has been shown in treadmill studies [1], [2], [3], [4].

The EEG and motion data used for this analysis were collected during performance of a cognitive task in an interactive VR environment. For the task, participants performed a classical n-back task [5], [6] where they virtually moved a sequence of colored balls using a single hand controller to receptacles on their left or right according to the current ball's color in the sequence [7]. Thus, the physical movements and associated artifacts can be stereotyped into reaching with left or right lateral movements. The stereotyped movement data were used to design a warp correlation filter (WCF) that estimates and removes the movement artifact from each motion trial. The approach was evaluated by correlating the EEG signals before and after artifact suppression with the movement data, and the impact of the artifact suppression on task classification performance was assessed.

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II. MATERIAL AND METHODS

A. Participants and Experimental Setup

Fifteen participants (ages 18-35 (mean 24.73), 4 female) were recruited to participate in the experiment, which was approved by the Institutional Review Board of Old Dominion University. The HTC VIVE hardware system primarily consists of a motion-tracked headset display, two motion-tracked hand controllers, and two "lighthouse" base stations that are capable of providing 6 Degree of Freedom (6DOF) tracking.

The EEG cap was placed on the participant's head and the EEG electrodes were filled with electrolyte gel. The electrode cap was then covered with a protective plastic hair dressing cap to insure that the gel did not seep onto the VR headset, and the VR headset was positioned over the EEG cap. The wireless EEG amplifier was placed in a shoulder strap on the participant's back. The configuration of the experimental equipment on a participant (excluding the protective plastic hair dressing cap) is shown in Figure 1.

Fig. 1. Configuration of the experimental equipment on a participant (excluding the protective plastic hair dressing cap).

After the EEG and VR equipment was positioned, participants grasped a VIVE hand controller in the dominant hand. Participants were placed in a standing position approximately

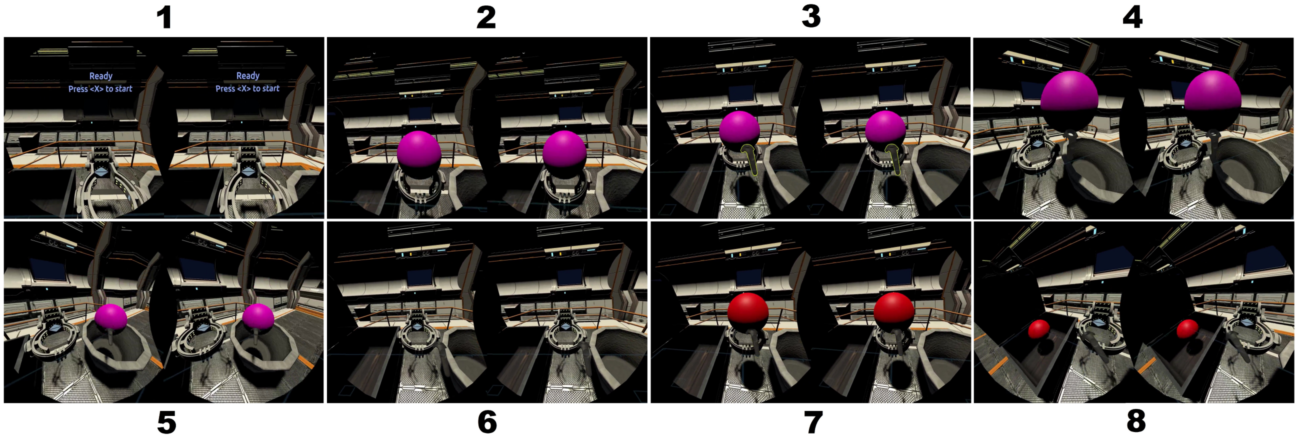

Fig. 2. Screen captures of the n-back task using colored balls in a virtual environment developed for the pilot study. Each frame represents the binocular view as observed through the VR headset.

1 meter in front of the recording computer, within the VR workspace.

B. Experimental Task

Stimuli are a series of colored balls presented on a virtual podium in the VR environment. Following [7], each ball is colored red, blue, purple, green, or yellow. A ball receptacle is placed to the right and left of the participant in the virtual environment. The target receptacle was shaped as treasure chest for placement of the target balls. For a particular run, the participants task was to pick up a the virtual ball from the podium directly in front of them using the hand controller and move it to the target receptacle if the current ball color matched the color of the ball presented N trials before and to the opposite receptacle otherwise. Screen captures illustrating one trial of the task are shown in Figure 2.

Participants completed a practice block to familiarize themselves with the VR system and the n-back task. Following the practice block, participants performed a series of three experimental blocks in randomized order: 0-back, 1-back, and 2-back blocks consisting of 4 runs each.

Each experimental run consisted of a random sequence of 20 balls, each of them remaining visible for 4 seconds, immediately followed by the onset of the next ball. Only a single ball is displayed at any given time and an auditory tone is presented with the appearance of each new ball. Participants were required to respond to all balls in each run. The order of the experimental blocks were counterbalanced across participants. For each participant, the target receptacle locations were counterbalanced to avoid biases that may be due to lateral movements. The software to reproduce the experiment is available in an Open Science Framework repository (https://osf.io/yhtz8/).

C. Data Collection

Each participant wore an 8-channel electrode cap (g.LADYBIRD, Guger Technologies) with active electrodes positioned based on the international 10-20 system [8]. Specifically, electrode positions F3, Fz, F4, C3, C4, P3, Pz, P4 were used based on neural activations from prior EEG and fMRI studies [9], [6]. EEG was collected using an 8-channel wireless biosignal amplifier (g.MOBIlab, Guger Technologies), grounded and referenced to linked earlobes, and digitized at a 256 Hz.

The position of the VR headset and the controller were also tracked and digitized at 32 Hz. Communication between the VR software (developed in Unity [10]) and the BCI2000 EEG recording software was performed via UDP communication using the application connector in BCI2000 [11].

D. Data Analysis

The EEG data were segmented by 4-second ball-presentation intervals (i.e., trials), yielding 240 total trials (4 runs X 3 conditions X 20 balls per run) per participant. The last trial of each run was excluded from the analysis due to a software issue that prematurely terminated data collection, which resulted in 228 total trials per participant for analysis.

Inspired by [2], a technique referred to as a warp correlation filter (WCF) was applied to suppress the stereotyped EEG movement artifacts. Because individual movements can vary slightly compared to the stereotyped movement, this approach applies time warping to best represent the movement time-course. Specifically, for each 4-second trial interval, a single dimension of movement data (x, y, z, or resultant direction) from the headset was time warped so that the start, end, and either maximum or minimum position (depending on the receptacle location) would be aligned in time. The resulting time warping was then applied to the EEG data for the corresponding trial.

Pearson's correlation between the movement data from each ball-presentation interval was computed and ordered from highest to lowest. The EEG data corresponding to the 6 highest-correlated movements were averaged to create the stereotyped artifact for each movement. This threshold was empirically determined to be optimal after evaluating up to the 20 most-correlated movements in the average. The resulting stereotyped artifact was subtracted from from the warped EEG data and the result was then de-warped to the original timescale by inversely applying the warping time vector. This process was repeated for the remaining movement dimensions of both the headset and hand controller. The flow diagram for this procedure is shown in Figure 3.

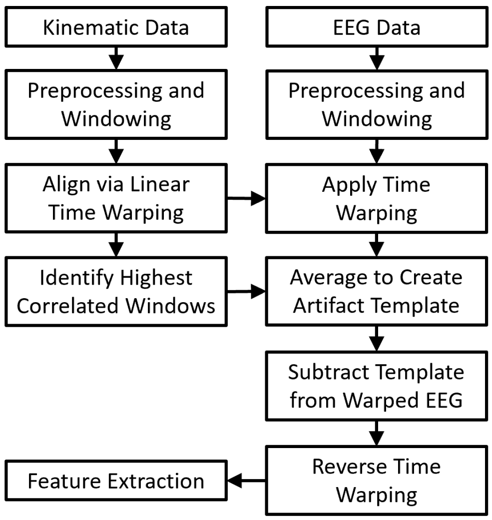

Fig. 3. Flow diagram of the movement artifact suppression procedure.

E. Validation

Pearson's correlation between the pre- and post-WCF EEG data and the hand-controller position data for the x, y, z, and the x-y-z resultant position, respectively. To assess the impact of the WCF on the classification of workload level from EEG, a feed-forward artificial neural network (ANN) with 1 hidden layer and 100 hidden nodes was trained on pre- and post-WCF EEG data, respectively. To further reduce high-frequency artifacts ($>$ 30 Hz) for classification, a bipolar reference was computed using each adjacent electrode pair, resulting in 8 bipolar channels. For each 4-second trial, spectral features were computed from all channels using Welch's method with 1-second windows and 60% overlap. To remove occasional artifacts that were not produced by stereotyped movements, a Hampel outlier filter was applied to the spectral features. If a given feature observation was greater than 9 standard deviations from the surrounding features within a 4-second window, the feature observation was replaced by the mean of the 6 surrounding temporal feature observations. The resulting frequency bins from 0 to 30 Hz were applied to the classifier.

III. RESULTS

A. Stereotyped Movements

Figure 4A shows the stereotyped movement paths for 4 representative participants. While the movement paths are markedly different for each participant, the respective left and right paths are highly-consistent for each participant. Figure 4B shows the left/right hand movement trials from a representative participant. The upper traces show all movement trials aligned by movement onset. The lower traces show the corresponding movement trials after time-warping, further illustrating that the movements are highly-stereotyped.

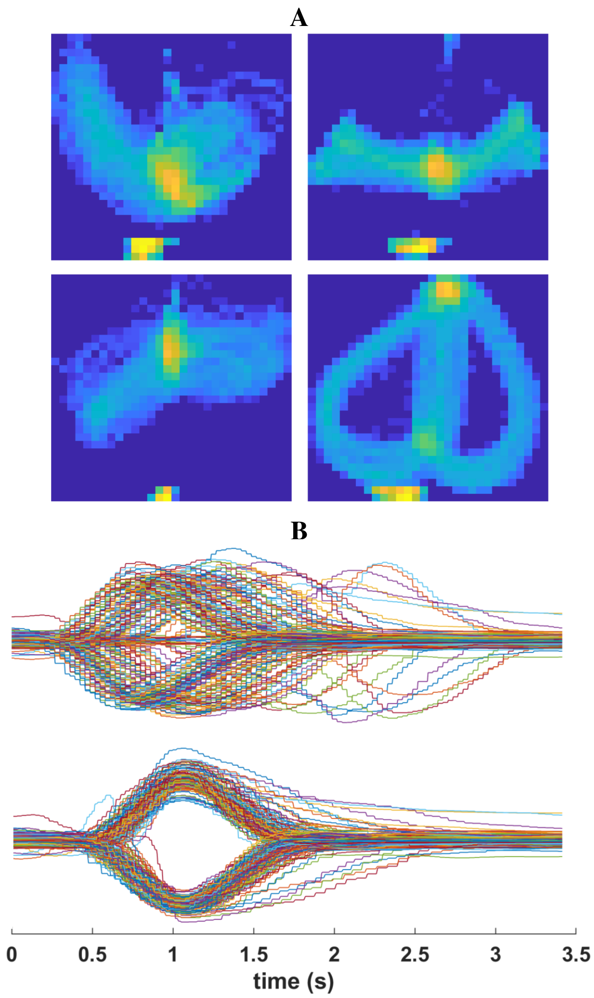

Fig. 4. (A) Density plots representing the x-y hand controller and headset positions during the task for 4 representative participants. The focal density at the bottom center represents the headset location; the upper focal density represents the location of the podium. (B) All data left/right hand movement trials from a representative participant. The upper traces show all movement trials aligned by movement onset. The lower traces show the corresponding movement trials after time-warping.

B. Warp Correlation Filter

Figure 5 shows representative time traces of the hand-controller position data and the pre- and post-WCF EEG. It is observed that transient EEG events visually correlate with the hand movements and the WCF is effective at suppressing the movement artifact at each movement interval.

Figure 6 shows the Pearson's correlation between the resultant movement data and the EEG from each bipolar channel, pre- and post-WCF. It is observed that the pre-WCF correlations are larger in the frontal channels and that the WCF effectively minimizes correlation with the movement data for all channels.

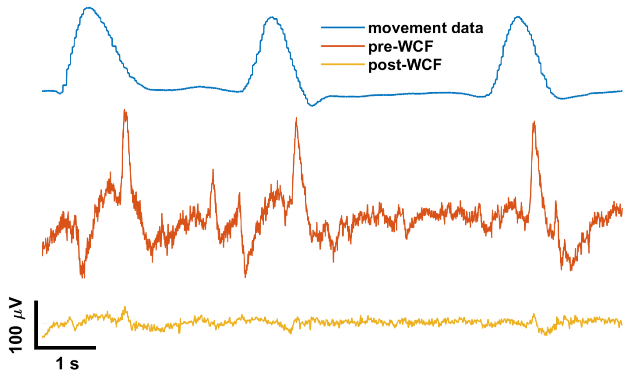

Fig. 5. Representative traces of the resultant movement vector, pre-WCF EEG from a single channel, and post-WCF from a single channel. The movement data is scaled to arbitrary units for visualization.

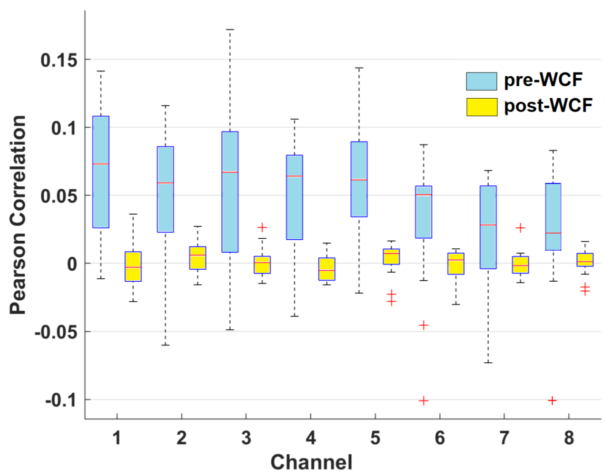

Fig. 6. Boxplots across participants of the Pearson's correlation between the resultant movement data and the EEG from each bipolar channel, pre- and post-WCF.

C. Workload Classification

Figure 7 Shows the ANN workload-level classifier performance using pre- and post-WCF EEG. It is observed that the suppression of the movement artifacts using the WCF approach does not have a drastic effect on the overall classification performance.

IV. DISCUSSION

In order for EEG to be considered as a viable sensing option in VR headsets, it is imperative to effectively counteract the movement artifacts that traditionally plague EEG recordings. The proposed approach exploits the fact that many interactive VR applications (e.g., for task training or gaming) inherently generate highly-stereotyped movements, and thus predictable EEG artifacts corresponding to these movements. The results indicate that this relatively straightforward approach is highly effective at suppressing movement-related artifacts in EEG.

As with any artifact suppression approach, care must be taken to ensure the result is not adversely affecting the

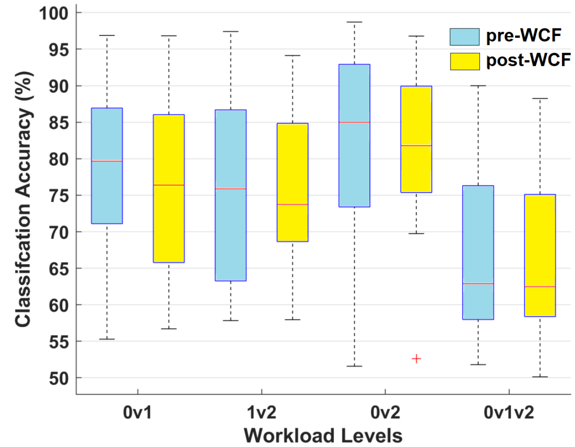

Fig. 7. Boxplots of the ANN classification accuracy across participants for each combination of workload levels, pre- and post-WCF.

desired signal features. While these results were produced in an offline analysis, a similar approach could be applied in an online scenario using calibration data and/or unsupervised learning. However, the classification results suggest that it may be possible to forgo active suppression of such low-frequency movement artifacts if the task-related EEG activity is sufficiently outside the spectral range of the offending movement artifacts.

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