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Enabling Free Movement EEG Tasks by Eye Fixation and Gyroscope Motion Correction: EEG Effects of Color Priming in Dress Shopping

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ABSTRACT The electroencephalogram (EEG) is a widely used tool for the non-invasive monitoring of the brain. However, it is very susceptible to motion artifacts, and current EEG studies are restricted to experiments where participants are stationary or perform only constrained movements, such as treadmill walking. This paper proposes a new multi-modal sensing approach for analyzing EEG collected during naturalistic free movement tasks. Co-recorded wearable eye-fixation and gyroscope data are used to identify times of interest for analysis and times of motion, and the EEG is then only analyzed during the short time periods when the eyes are fixated on wanted stimuli and there is a natural pause in the motion of the subject. We demonstrate the technique in a real-world task where subjects move round a clothes shop. This shows that in all cases, more than 65% of the time localized EEG could be analyzed, despite the free movement nature of the task. Furthermore, it can be used to demonstrate the effects of color priming in clothes shopping. We show an increase in left frontal EEG activity when participants view products matching the color background of the shop environment.

INDEX TERMS EEG, motion artifact, color priming, clothes shopping.

I. INTRODUCTION

Electroencephalography (EEG) is the monitoring of a subject's *brainwaves* by placing small electrodes on the scalp, and is of key use for non-invasive brain interfacing [1]. A key advantage of the EEG over other neuroimaging techniques is that it is in principle a portable technology, with the electrodes and instrumentation box being small and lightweight using modern microelectronics. As such it gives significant potential for out-of-the-lab use and studying the brain in motion, in naturalistic environments. To this end ambulatory EEG units have been available for many years [2]. However, historically the EEG has been limited to situations where subjects are not moving, as movements introduce substantial artifacts into the collected EEG traces and obscure the wanted brain-related information [1]. The motivation of this article is to provide a new method for performing EEG studies where subjects are moving, using multi-modal sensing combining EEG, eye tracking, and gyroscopes to differentiate between EEG epochs which are of interest for analysis, and EEG epochs which are contaminated by motion.

In recent years there has been a significant amount of research interest towards creating *wearable* EEG units, which allow *real-world* neuroimaging while subjects are moving around [3], [4]. Many of these efforts have focused on improving the EEG hardware by: removing the long recording wires between the electrodes and the instrumentation box which pick-up large amounts of interference [5]; giving higher input impedances to allow gel-free recordings [6]; incorporating real-time impedance monitoring [7], [8]; and enabling active electrodes for quicker and easier set up [9]. This has been combined with improvements in software algorithms for the removal of motion artifacts, particularly using Independent Component Analysis (ICA) techniques [10]. As a result several studies have now demonstrated the

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ability to extract EEG parameters during modest amounts of movement. For example, [11] and [12] have demonstrated the recording of evoked potentials, below the free running EEG noise floor, while subjects walk on a treadmill. The study of EEG dynamics during cycling has also been demonstrated [13], [14].

To date such studies have generally been performed on treadmills and exercise bikes. These are very good for semi-controlled movements and repetitive movements, and demonstrate substantial potential for use in rehabilitation applications [12], but do not capture all of the dynamics of unconstrained free movement. For example, walking on a treadmill is only in a straight-line, generally at speeds slower than real-world walking, and does not account for more naturalistic movements which will include many stop-starts, movements in different directions, impulsive movements, movements at different speeds, and similar. Studying the EEG during free movement of the subject is significantly more challenging. Further, in wearable EEG there is a strong emphasis on a reduction in the number of electrodes used to give units which are inconspicuous, and quick and easy to set up, particularly by non-specialist users. This acts against the use of ICA and similar blind signal separation approaches which favor high electrode counts as one source component is identified per input EEG channel. Many in-lab computational neuroscience studies use 64 or more channels as standard. While there can be some debate on the precise number of channels that are acceptable for *wearability*, there is a clear need to allow motion-robust EEG experiments which do not rely on having high numbers of electrodes present.

In this paper we investigate EEG dynamics during a fully free movement task, demonstrating that it is possible to extract information from the EEG while using low channel count EEG units without relying on ICA and similar approaches. Our new approach is based on multi-modal sensing, combining a wearable EEG unit with a wearable eye tracker to allow highly time localized analysis of the wearable EEG data. We make use of co-located motion measurements, and in particular the gyroscopes present in both wearable units, to allow highly accurate synchronization of the two devices. This overcomes the issue of synchronizing two separate wearable units which have no physical connection, no input ports for aux/sync/trigger signals, different rates of clock drift, and no Lab Streaming Layer [15] or similar set up. Using the highly synchronized EEG and eye tracking data we then analyze the EEG only during the short time periods when the eyes are fixated on a wanted target stimuli. Thus, although the subject is free to move in general, there are still many times when no motion is present or when no motion interference manifests in the EEG traces, and it is only motion artifact contaminated EEG which occurs within the short duration eye fixations which need to be excluded from analysis.

Our results and new methodology provide two new contributions. Firstly, with simultaneous motion and EEG recordings we are able to quantify the motion contamination of EEG during free movement. By considering EEG epochs lasting for only 100 ms during fixations on wanted targets we find that no more than 35% of the during-fixation EEG data has to be discarded due to motion contamination. Moreover we quantify how much movement is required to generate a motion artifact in the EEG, showing that movements in nodding and rolling motions have statistically significantly lower motion thresholds for artifact induction. Secondly, we validate the approach by investigating EEG responses during a free movement shopping task as a representative example of an everyday activity. We show that changes in engagement measured via EEG frontal asymmetry measures can be detected, and that these differ depending on whether the user is *primed* with different colors within the shopping environment. Priming is a phenomenon in which exposure to one idea can subconsciously provoke related ideas [16] and we use different color garments and environments to investigate whether the color of the environment influences (or *primes*) the participants' responses to the garments available within the environment.

Section II introduces our experimental methodology, giving details on the multi-modal sensing used to allow the EEG frequency content to be analyzed to within a resolution of 100 ms, overcoming issues with the alignment of multiple sensor data, hardware clock drift, and very short duration analysis epochs. Results are presented in Section III where we quantify the amount of motion which induces a motion artifact in the EEG trace, and the amount of time the EEG is corrupted by motion during our free movement task. These results are then discussed in Section IV where we investigate the effect of color priming during free movement shopping and show an increase in left frontal EEG activity when participants view products matching the color background of the shop environment.

II. METHODS

A. MULTI-MODAL SENSING

Our proposal for low channel count EEG analysis during naturalistic movements is to perform a highly time localized analysis: by only considering the short sections of EEG where the participant is looking at a wanted target in the environment, data from other time points is not needed. Thus it is not significant if motion is present at these other times. By using simultaneous mobile eye tracking, Areas Of Interest (AOIs) can be identified in the environment, and analysis of the EEG only performed when the eyes are fixated on one of the AOIs.

The key technical challenge with this approach is that it requires simultaneous mobile EEG and mobile eye tracking with very accurate synchronization between the two wearable equipment items as fixations on AOIs are typically very short in duration (235$\pm$62 ms in our experiment). Mobile EEG and mobile eye trackers are now readily available, however, being battery powered there is no direct connection or synchronization between the two, and the two recordings are independent of one another. No ports for TTL triggers, or protocol

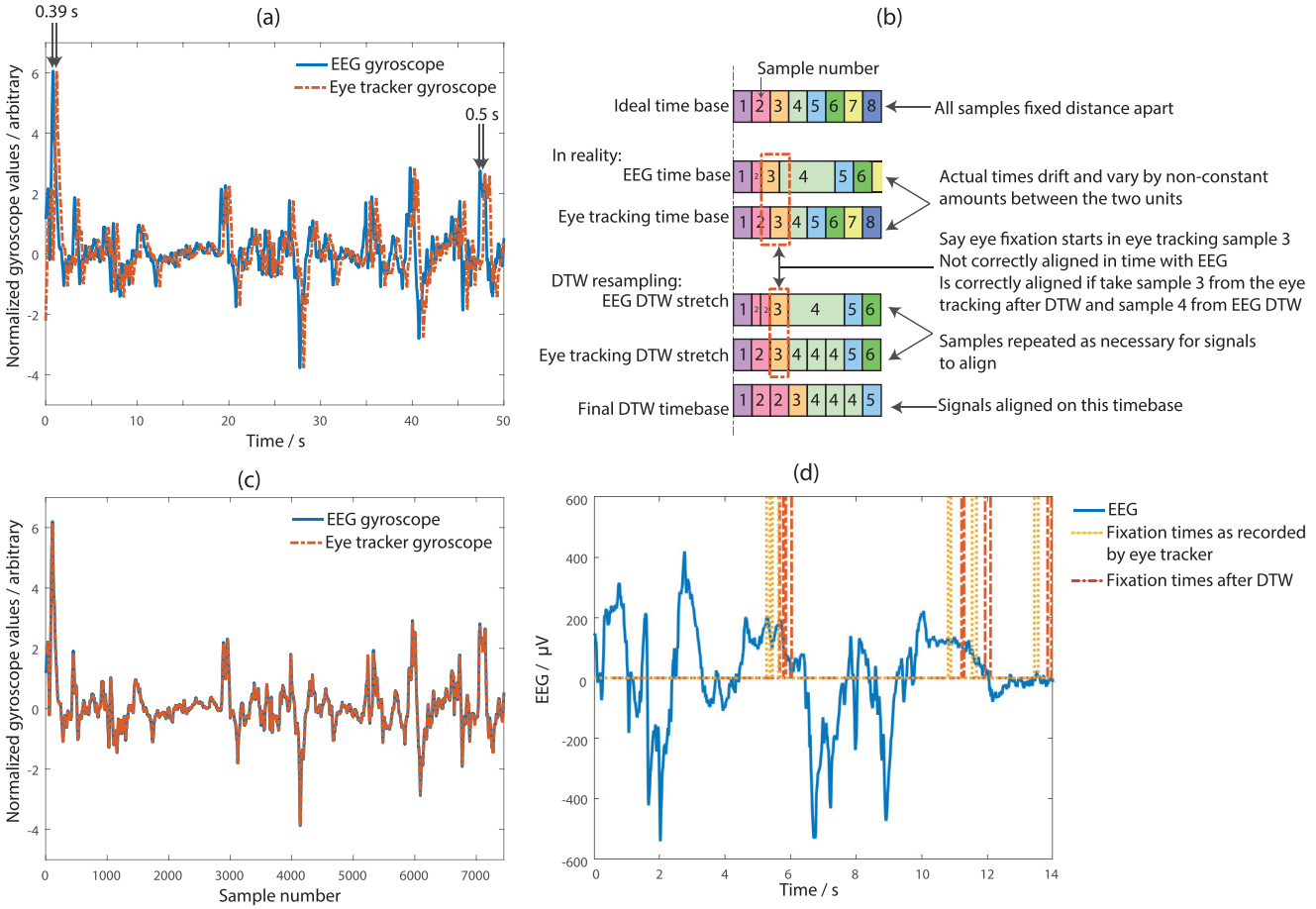

FIGURE 1. The mobile eye tracker and mobile EEG time stamps drift apart over time, with the rate of drift varying with environmental conditions. This is corrected by Dynamic Time Warping (DTW) applied to the gyroscope signals to closely synchronize these in time. The time warping parameters calculated using the gyroscopes are then applied to the EEG and fixation data to align these in time, given the dynamically changing drift rate measured from the gyroscopes. (a) Gyroscope motion signals from both units start in synchronization and then drift apart. (b) The DTW procedure places all signals on a common time base and allows time points to be mapped between different time bases. (c) Sampling drift is corrected by DTW. (d) Fixation times as measured by the eye tracker are projected on to the EEG time base using the gyroscope calculated DTW parameters. This corrects their position and synchronizes the data from the two different measurement units to allow a highly time localized analysis of the EEG data.

for synchronization are provided as they typically are with non-mobile devices. Protocols such as NTP (Network Time Protocol) can be used at the computers which receive the wireless bio-signal traces, but NTP signalization is typically only to the 10's of milliseconds [17]. This is suitable for gross equipment synchronization, ensuring devices do not drift apart over time, but not for the very tight synchronization required in our experiment.

Further, and most importantly, both units will suffer from differing amounts of clock drift, meaning that although both should sample the incoming signals at a fixed and constant rate, the actual rate varies over time with the battery voltage, temperature and similar [18]. This drift is not fixed, and will vary during the course of a recording preventing synchronization of the raw data by a bulk shift alone. Lab Streaming Layer [15] is a popular method for overcoming these issues for lab based equipment, but it is intended for synchronization over a local network of computers with NTP available, not highly portable wireless units with no access to an NTP server from the wireless device itself. Moreover, it requires drivers, with neither of our highly wearable devices being supported at the time of performing this work.

To overcome these issues we propose a highly accurate, data driven, post-hoc signal alignment by employing the co-located gyroscope sensors on both devices. (The EEG unit has a two axis gyroscope, and the eye tracking unit has a three axis gyroscope, see Section II-C.) Both being mounted on the head of the subject, the different gyroscopes to a close approximation record the same motion trace. This means the drift in the sampling rate between the devices can be measured from the gyroscopes, and this measured drift used to correct and accurately align the co-recorded EEG and eye tracking data. An example of this procedure is shown in Fig. 1.

For each data record the two gyroscopes were first bulk aligned by shifting them by a time delay corresponding to the maximum cross correlation time, giving two signals which are nearly in synchrony, but drift apart over time

as the sampling rate varied (Fig. 1(a)). This varying rate was corrected by applying Dynamic Time Warping (DTW) to the two gyroscope traces (Fig. 1(b)), implemented using the Matlab `dtw` function described in [19]. DTW gives indices for applying a zero-order-hold to *stretch* the two signals so that the gyroscope signal points align in time (Fig. 1(b)). For example, if the EEG gyroscope samples were originally at times [0 0.078125 0.015625 0.0234375 ...] (with sampling frequency 128 Hz) these might become [0 0.078125 0.015625 0.015625 0.015625 0.0234375 ...] where the 0.015625 sample is repeated three times in order to align with the EEG time base with eye tracking time base.

The indices calculated for the EEG unit gyroscope were then used to re-sample (stretch) all of the signals collected by the EEG unit: the EEG, EEG gyroscope data, the time base as reported by the EEG recorder, and the frequency band powers (calculated using the raw EEG input as described in Section II-B). Similarly the indices calculated for the eye tracking gyroscope were used to re-sample all of the signals collected by the eye tracking unit: times at which the eye looked at each AOI, eye tracker gyroscope data, and the time base as reported by the eye tracking unit. The result is that all of the raw collected signals, and the EEG band powers calculated from the raw EEG signal, now share a common *stretched* DTW time base ((Fig. 1(c))). From this, fixation times in the eye tracking time base can be mapped to times in the EEG time base, accurately aligning the timing so that the correct period of EEG is analyzed during each fixation (Fig. 1(d)).

B. EEG FREQUENCY BAND EXTRACTION

The next challenge to overcome is the analysis of very short EEG epochs, down to 100 ms as the EEG present during a fixation on an AOI. Typically the Fast Fourier Transform is used for EEG analysis, and the EEG epoch duration set as ten times the time period of the lowest frequency to resolve. For 8 Hz alpha activity this would be 1.25 s, which would mean our highly time localized analysis would not be possible.

Instead, to give greater control over the time-frequency localization performed, we extracted the energy in the EEG trace at each time point using a first order Butterworth filter with cut-offs at the wanted EEG frequency band edges. This is implemented with the `filtfilt` command in Matlab to give zero group delay so there is no temporal shifting of the frequency information due to the filtering process. The time-frequency localization provided in the alpha 8–12 Hz band is shown in Fig. 2 where frequencies are constrained to be within the passband of the filter (8–12 Hz), while the time support is the duration of the impulse response, with a full-width half-maximum of 78 ms, showing that frequency information can be localized in time to within the 100 ms fixation duration we consider. This comes at the cost of the non-flat passband seen in Fig. 2(a) for the extraction of frequency information. We have traded reduced frequency-localization in order to obtain better time-localization.

To avoid distorting the power spectrum during dynamic time warping this procedure is applied to the raw EEG data as recorded, prior to applying the DTW procedure from Section II-A, with the DTW also applied to the output of our Butterworth filters. The DTW procedure then only affects where the fixation time epoch to consider starts and ends in terms of the samples to select and sum.

Using the filter output the instantaneous EEG energy is then found in dB as

$$e_{dB} = 10 \log_{10} \left(\text{Filter output}^2 \right) \tag{1}$$

to give a sample-by-sample estimate which can be summed over any desired time span to find the total energy present in that span. Fig. 2(c) shows how this alpha band energy extraction (in EEG channel F3) compares to a Fast Fourier Transform approach with 1.25 s Hamming windows, and 50% overlap between windows. The Fourier Transform envelops our instantaneous band power extraction.

C. WEARABLE EYE TRACKING AND WEARABLE EEG

To perform our natural movement experiment participants were set up with both a wearable eye tracking and a wearable EEG unit. Eye movements were recorded using the wearable Tobii Pro Glasses 2, with calibration performed before entering the experiment area. This eye tracker was fully portable, mounted into the frame of a pair of glasses, and contained one forward facing scene camera, four eye facing cameras, a three axis gyroscope and a three axis accelerometer. The glasses weigh only 45 g and have a sampling rate of 50 Hz.

EEG was performed using the Emotiv Epoc+ as a representative EEG amplifier used for mobile and out-of-the-lab experiments [20]. Fourteen channels (AF3, F3, F7, FC5, T7, P7, O1, O2, P8, T8, FC6, F8, F4 and AF4, referenced to P3 and P4) were recorded at 128 Hz. The EEG unit included a two axis gyroscope in the instrumentation box at the back of the head. All electrodes were connected to the scalp using the Emotiv standard saline soaked sponges, with the electrode connection quality checked at the start and end of the experiment. All data was filtered between 0.16 and 30 Hz using first order zero phase delay Butterworth filters, with an additional 50 Hz noise filter to remove mains interference, prior to analysis in Matlab.

The eye tracking glasses were put on first to allow them to be positioned without affecting or accidentally moving the EEG electrodes. The average location of both eyes was used as the tracked signal and this raw eye tracking location data was median filtered, with a 3 sample window. Eye fixations, defined as a stable position of the eye for a minimum of 60 ms [21], were calculated using the Tobii I-VT algorithm [22]–[24]. This eliminated saccade movements, and adjacent fixations which were less than 75 ms and 0.5° apart were merged into a single final fixation, with these values taken as the Tobii I-VT algorithm defaults [23]. Only fixations greater than 100 ms in duration were then considered for analysis. These fixation times were manually mapped on to 31 AOIs in the retail environment (Section II-D).

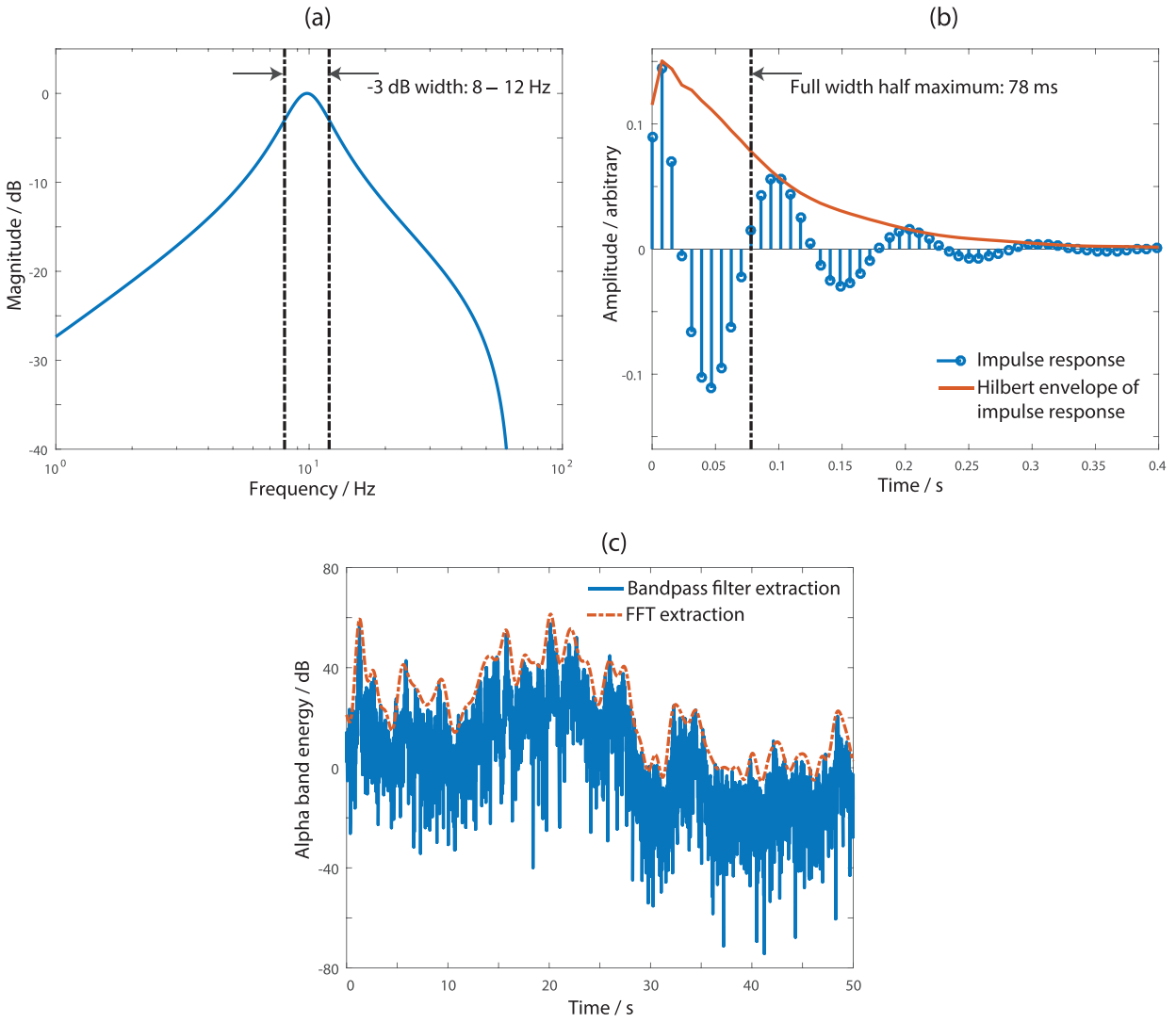

FIGURE 2. **The time-frequency localization used to extract alpha band activity during fixations as short at 100 ms uses a filter rather than Fourier approach to obtain better time-localization at the cost of frequency-localization. (a) Frequency-localization is concentrated within the non-flat pass-band. (b) Time-localization is concentrated within the full width half maximum of the impulse response. (c) Comparison of energy estimated from the bandpass filter with a 78 ms full width half maximum time support and a Fast Fourier Transform (FFT) method using 1.25 s windows of data. This Fourier transform time support is selected to allow 10 cycles of the lowest frequency of interest (8 Hz) alpha to be present in each calculation window.**

Twenty-three AOIs were on dresses (one on each different dress), two on the mannequins used for priming, two on the pictures used for priming, and four not used in this study. This allowed the fixation times when the participants were looking at primed color and non-primed color dresses to be extracted. The EEG was then analyzed only during these fixation times.

As both units contained gyroscopes, we were able to use this data to accurately align the traces (Section II-A), and for the first time quantify motion contamination of free movement EEG traces. The presence of motion was identified from the 3-axis eye tracker gyroscope by applying a threshold from 0–360 degrees per second (dps) to produce a yes/no flag indicating whether the absolute gyroscope signal was above the threshold for each point in time. The presence of a corresponding motion artifact in the EEG was identified automatically to avoid manual interpretation biases by applying the EEGlab continuous artifact rejection function `rejcont` to all channels of the EEG. `rejcont` identifies artifacts from the EEG spectrum between 20 and 40 Hz, in 0.5 s epochs, marking sections where the content is above a set energy threshold as being artifactual with a yes/no artifact present flag [10]. In this work the detection threshold for the EEG was swept from 5 dB to 10 dB to vary the sensitivity with which EEG artifacts were detected.

Combined with the 360 different thresholds for detection of motion from the gyroscope data, this gives a 360×5 array of motion identification flags for each time point in the collected data series. The percentage of time when the two yes/no flags agree for each combination of detection thresholds was worked out for each subject, and then averaged to give

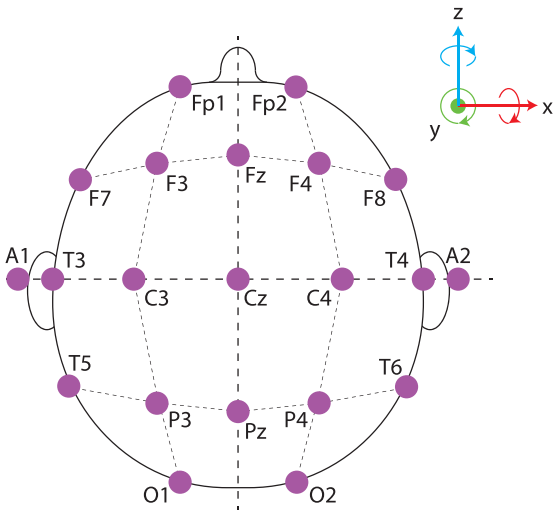

FIGURE 3. The EEG electrode 10–20 positioning system with the motion axes directions superimposed.

an overall motion sensitivity result. The directions of the gyroscope motion axes are shown in Fig. 3, with the x axis corresponding to a nodding movement, y axis corresponding to a shaking the head movement, and z axis to a rolling the head from side-to-side movement.

D. NATURALISTIC MOVEMENT TASK AND COLOR PRIMING

To validate and use our new multi-modal sensing approach we aimed to extract information from the EEG during a naturalistic movement task, which may contain a range of movements and stationary periods. We selected a shopping environment as an exemplar of a real-world task where subjects will be moving and interacting with the environment, but not necessary moving constantly as they would if on a treadmill. Previous studies have examined EEG and non-wearable eye-tracking analysis of consumer responses in dress shopping in lab-based environments [25], [26], but not while moving about a physical shop.

For this experiment we created a physical retail store to allow participants to move about in a naturalistic way, while giving the experimenter control over the stock displayed, and colors presented. The retail environment consisted of two walls of dresses, with a number of mannequins, pictures, and accessories as shop decoration under neutral white lighting. This environment was populated with nine blue dresses, six red dresses and three pink dresses, together with five additional dresses in a neutral color. Further, we used three variants of the shop with different color *primes* present in the shop background. It is well known that consumer purchase decisions are based on more than just the tangible object, they are based on the total product, of which the retail environment is an important feature. In some circumstances the atmosphere of the retail environment can be more influential on the purchase decision than the product itself [27]. Priming is a phenomenon in which exposure to one idea can subconsciously provoke related ideas [16].

We incorporated color priming as an additional measure to verify the EEG data as it is particularly important within the fashion industry, with color trends often forecasted up to two years ahead of each season, with heavy influence on the fashion product design process [28]. It has been established that color impacts cognitive interpretations as well as affective evaluations of products [29], subsequently influencing consumer behavior. Color priming of the retail environment has been found to increase the consumer likelihood of choosing a product that matches the color that they have been primed towards [30]. Reference [30] found increased recall and preference for products of a particular color, after repeated exposure to that color while walking around a supermarket. We were similarly looking for an increase in approach emotional response towards dresses (products) of the color that match the prime effect in the room.

To assess emotional response, the motion free EEG epochs during fixations on dresses was inputted into the widely used Davidson's model of emotion [31]–[35]. Here an increase in activity in the left hemisphere of the pre-frontal cortex is indicative of a positive approach emotional response and we compare the inter-hemisphere frontal asymmetry in the alpha band as an EEG measure of emotion in the different priming conditions. This is calculated as the root-mean-squared values from the bandpass filter outputs (Section II-B):

$$\text{Asymmetry} = 20\log_{10}\left(\frac{1}{T}\sqrt{\sum_{T}\text{Filter out right channel}^2}\right) - 20\log_{10}\left(\frac{1}{T}\sqrt{\sum_{T}\text{Filter out left channel}^2}\right) \quad (2)$$

where T is the duration of the fixation during which the EEG is taken from. The same measure was calculated from the EEG baseline period before the start of the experiment (Section II-E), taken as the median value from each 100 ms epoch during one minute of stationary time before the start of the experiment. For each subject this baseline was subtracted from the during fixation asymmetry measure to normalize for different levels of emotional valance before starting the experiment. The expected change in asymmetry is highly localized on the head, with the most common electrode positions used for measuring engagement response being F3 and F4 [35]–[38].

A photograph of the shop with a blue priming, together with examples of how the priming was changed, is shown in Fig. 4. To allow priming of the subject the colors of the mannequins and pictures present were changed to be either blue, red or pink, matching the dresses present. This is classified as repetition priming, as repetition priming simply refers to the increasing amount of exposure to the prime that the participant receives. Note that we do not analyze

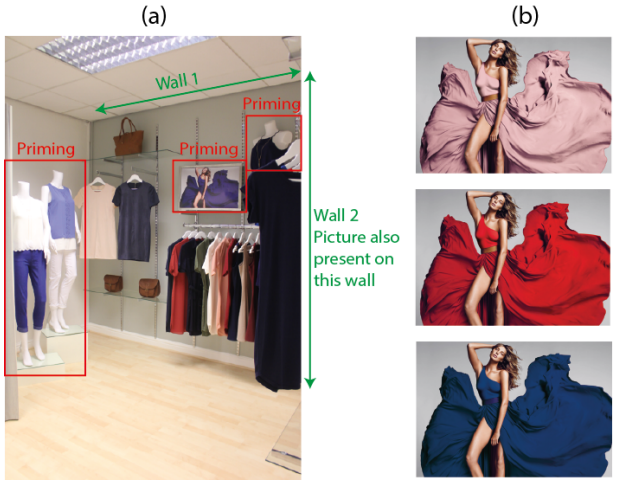

FIGURE 4. The retail environment used. (a) Two walls of dresses with mannequins and pictures used for subject priming. (b) Pictures changed between pink, red and blue priming cases.

differences between the priming colors here, in this work we only consider whether the participant was looking a prime colored dress or non-prime colored dress. The dresses were all ones available in high street retailers, chosen to all be a single color with no pattern or multi-colored design. There were various styles of dress, each style was present in multiple colors. All other colors in the store design remained neutral, for example the walls were painted white and grey, the mannequin's bodies were white, and the plinths that the mannequins stood on were also white.

E. TASK AND PARTICIPANTS

Before starting the experiment participants had the EEG and eye tracking equipment set up (Section II-C) in an area where the shop was not visible to them. Before to entering the shop they spent 60 s in a neutral colored waiting area, remaining stationary, to allow a period of baseline motion free data to be collected. The entrance to the shop was arranged so that when the participant entered they would first see wall 1 of clothing (Fig. 4) and participants were instructed to walk into the shop and stop in front of wall 1 for a duration of their choosing, before then moving forwards to browse through the clothes as they would in a standard high street shop. During this phase they were told they could look at all of the clothes on this first wall, have a feel of the fabrics, or even hold the items up to see how they looked against themselves in the mirror. Participants were encouraged to use this phase to have a closer inspection of the clothes, to help inform their decision of which they might like to choose. When the participant felt they had had enough time to browse wall 1, they returned to the center of the room and stood to look at the clothes again from this short distance. They then turned to look at wall 2 and repeated the above procedure. Both walls were primed with the same color. The motivation for segmenting the experiment was for introducing a period where the participant was stationary in the middle of the task to allow the EEG data to be checked for validity, having a section where no motion artifacts would be present. The experiments lasted for approximately 6 minutes each.

Twenty-six participants aged 18–25 took part and were randomly split into one of the three priming colors. Participants were not informed that the store environment was different between different participants, or that the colors of pictures and mannequins clothes were selected to match or not match the dresses available. All of the participants were selected to be female, to fit a target demographic shopper of a millennial interested in dresses. This is the largest sector in the fashion industry [39]. All participants were also right handed to avoid inter-hemispheric differences, and had normal or corrected to normal vision. All experimental procedures were approved by the University of Manchester Research Ethics Committee.

III. RESULTS

A. MOBILE DATA SYNCHRONIZATION

On average the bulk delay between the two portable recording devices, found from the maximum cross-correlation between the gyroscope traces was 0.6 ± 0.4 s. To correct for non-constant drift between the two recording devices dynamic time warping was applied with an average of 0.21 ± 0.12 s required to align the records. (The precise amount of correction required was different for each record, and for different times within each record.) This average of the non-constant sensor drift rate corresponds to a speed of deviation between time as recorded by the two units of 53.6 ± 22.3 milliseconds per minute of recording. This shows that high time precision analysis of the wearable data is not possible without dynamic adjustments of the effective sampling rate, enabled here by the co-located motion sensors. Applying only a fixed delay, the EEG and eye tracking data would have drifted apart by >100 ms, our minimum fixation duration, within two minutes of recording. After this time using the raw eye tracking time stamps would result in analyzing an incorrect section of EEG data.

After applying DTW the correlations between the eye tracking gyroscope and the EEG gyroscope was 0.992 ± 0.009, that is, extremely high. Despite the eye tracking motion sensor being at the front of the head and the EEG motion sensor being at the back of the head, both record very similar motion signals. This demonstrates that the units are not moving in relation to one another, and that the whole head can be considered as a rigid moving body. It means that the full three axes of the eye tracking unit gyroscope can be used to investigate the motion threshold required to introduce a motion artifact into the EEG, not just the two axes included with the EEG unit gyroscope.

B. EEG SENSITIVITY TO MOTION

Motion times were identified by both thresholding the gyroscope signals and from examining the EEG trace for the presence of motion artifacts. Fig. 5 shows the percentage of time that motion detections from the two different signals agree

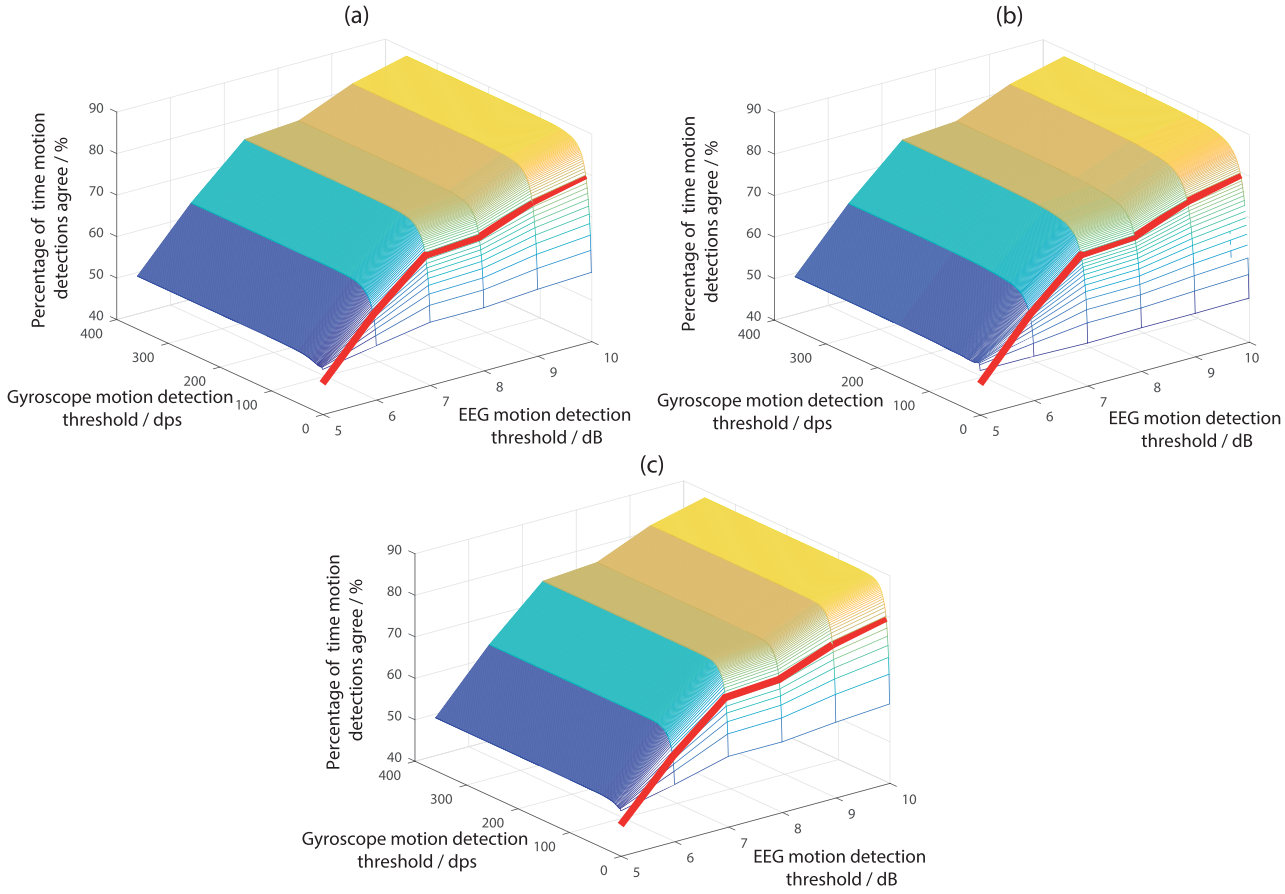

FIGURE 5. Agreement between when the gyroscope signals indicate motion is present and when an artifact is present in the EEG trace using different thresholds for detection. Red line indicates the gyroscope threshold to reach within 10% of the maximum agreement. (a) x axis of gyroscope used. (b) y axis of gyroscope used. (c) z axis of gyroscope used.

with each other, as different thresholds are used to require motion to be identified. The general form of the results is the same for all of the three axes of possible head movement. When the gyroscope threshold is very low, essentially the whole trace duration is marked as being motion. This leads to a low level of agreement with artifacts identified from the EEG. As the gyroscope threshold is increased, agreement with the motion artifacts from the EEG also increases, as the gyroscope gives a more realistic estimate of whether motion is actually present or not. At high gyroscope thresholds the agreement plateaus, as both the gyroscope data and EEG analysis agree when motion is not present. As the EEG threshold is increased the agreement increases further, as both methods identify fewer motion artifacts.

To compare the different axes for movement, also drawn on Fig. 5 is a red line where the agreement between the gyroscope and EEG motion agreement is 10% below the value at high gyroscope thresholds. This is used here as the trade-off in gyroscope threshold needed to not be too restrictive meaning the artifacts are not identified, and not too generous in just marking everything as an artifact. This 10% threshold value is an arbitrary choice to select the *corner* point in Fig. 5. The statistical results presented below are robust to any choice of threshold value up to 40%, with 10% used here to generate illustrative figures.

The average gyroscope threshold for different participants, for the different movement axes, is shown in Table 1. A one tail Mann-Whitney U test shows that the thresholds in the x (nodding) direction are significantly lower ($p < 0.01$, $r = -0.424$) than in the y (head shaking) direction. A second one tail Mann-Whitney U test shows that the thresholds in the x direction are themselves significantly higher ($p < 0.01, r = 0.753$) than the z (head rolling) direction. The inducement of motion artifacts in the EEG trace is thus most sensitive to nodding (x) and rolling (z) motions.

Fig. 6 illustrates example waveforms collected during each of the different types of head motion, showing the 14 recorded EEG channels and the Emotiv gyroscope signals in a controlled test where the subject was asked to nod, shake and roll their head respectively. Here the greater motion contamination from the rolling motion is seen, particularly as electrode FC6 becomes disconnected in this example.

C. MOTION CONTAMINATION DURING FIXATIONS

The fixation durations when looking at dresses which were the same color as the shop prime were 235±62 ms.

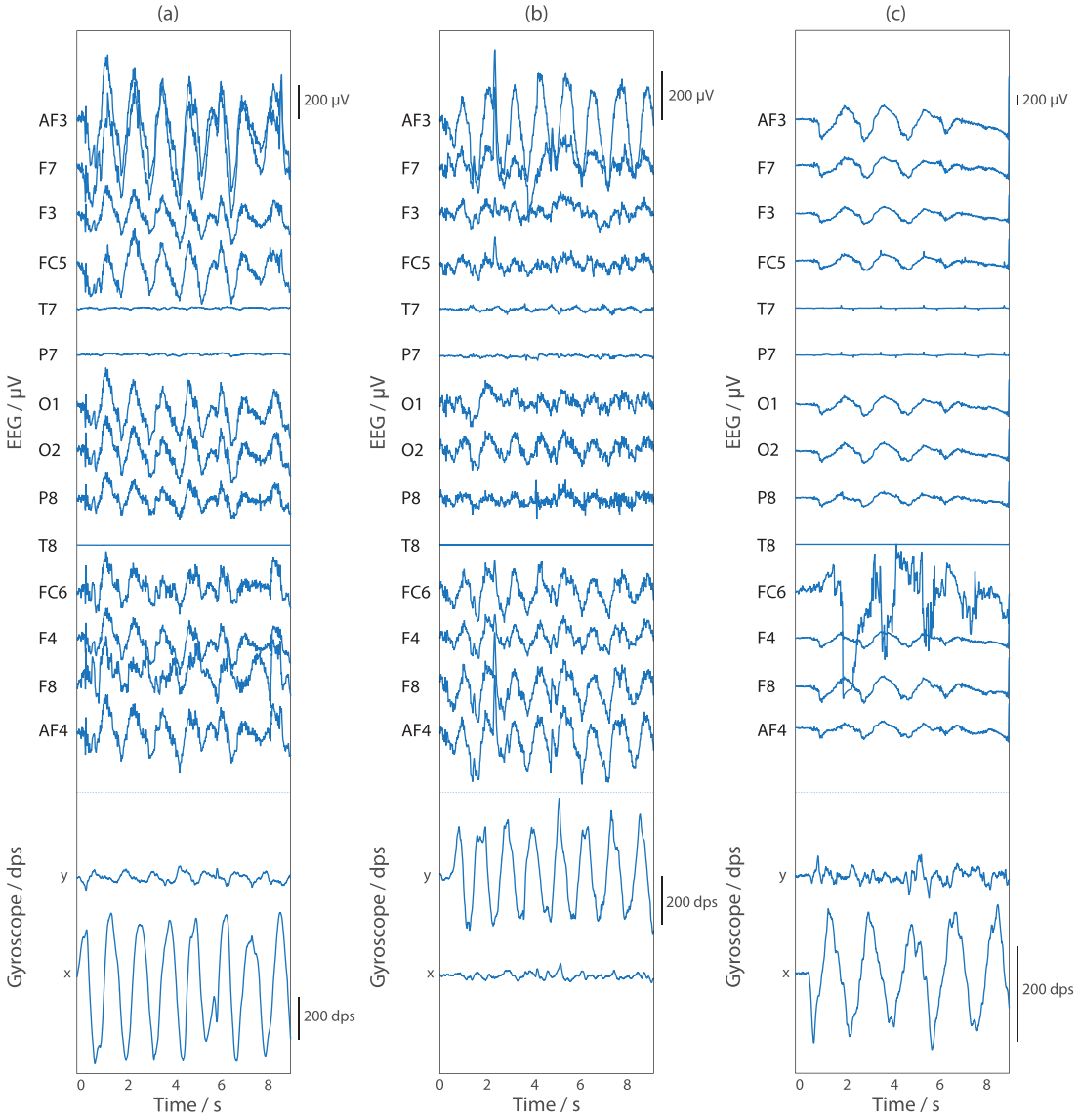

FIGURE 6. Example EEG and gyroscope traces recorded from the Emotiv during different types of head movement. (a) Nodding motion. (b) Shaking motion. (c) Rolling motion. Note that to be plotted side-by-side the scaling on each graph is different.

For non-prime dresses this duration was 233±78 ms, with no statistically significant differences present (t test, $p > 0.05$, $d = 0.031$). To analyze only EEG in these short duration fixation epochs it is first necessary to identify and remove fixations that contain motion.

Motion times were identified using the gyroscope data in the z direction with the thresholds given in Table 1 as the EEG was most sensitive to movements in this direction. The percentage of fixation epochs which had motion occurring in them, and the percentage of the total fixation duration which was corrupted by motion, are given in Table 2. It can be seen that even in the worst records no more than 35% of the fixations had to be discarded due to the presence of motion, with this corresponding to 21% of the time duration of the fixations. On average only 16% of the fixations were discarded. Although the EEG is in general very highly contaminated by motion due to the free movement nature of the task, due to the actual movement in the shopping task in the highly time localized analysis performed here the majority of the wanted short duration EEG sections are artifact free and can be used directly for analysis. If wanted, the 16% of EEG in discarded fixations could be processed using artifact removal algorithms to potentially re-include them, but this is not considered here.

In Table 2 no statistically significant differences are present between the prime dresses and non-prime dresses (Mann-Whitney U test, $p > 0.05$, $r = 0.044$) suggesting that the priming did not alter the motion of the subject. The distribution of artifacts is similar regardless of whether the participant is looking at a prime colored dress or a non-prime

TABLE 1. Gyroscope threshold corresponding to when a motion artifact is seen in the EEG data. All values in degrees per second (dps).

Participant	x	y	z
1	06	09	03
2	18	15	07
3	07	10	05
4	08	12	05
5	13	23	09
6	05	08	05
7	12	20	08
8	09	10	06
9	13	28	11
10	12	16	05
11	11	21	07
12	17	22	13
13	15	16	07
14	05	10	04
15	07	14	04
16	17	19	12
17	11	12	07
18	08	17	04
19	12	17	08
20	11	11	07
21	11	16	10
22	15	21	13
23	13	14	06
24	09	16	06
25	09	16	07
26	25	23	12
Mean	11	15	07
Standard deviation	05	05	03

TABLE 2. Percentage of fixation epochs which contain motion, calculated as both the number of epochs and the amount of total fixation time.

Participant	Number / %		Duration / %	
	Prime dresses	Non-prime dresses	Prime dresses	Non-prime dresses
1	33.33	33.91	20.83	18.42
2	13.04	17.50	04.93	07.62
3	22.73	20.10	13.00	08.20
4	31.34	21.88	10.57	11.09
5	08.47	19.32	03.04	09.73
6	00.00	04.92	00.00	02.24
7	02.78	11.62	01.85	05.19
8	09.52	12.68	07.45	07.51
9	35.48	09.55	20.74	03.31
10	30.00	20.18	11.02	08.47
11	16.10	17.77	06.77	06.51
12	13.00	07.00	05.05	03.04
13	12.68	13.33	08.77	08.09
14	19.74	15.29	09.94	07.28
15	25.08	30.25	07.27	08.06
16	20.62	09.36	09.47	04.09
17	14.67	12.58	04.18	03.63
18	12.04	15.73	05.23	08.56
19	06.58	21.43	03.66	09.56
20	10.53	19.91	05.05	08.46
21	11.41	14.81	04.74	05.61
22	29.82	11.03	17.27	08.77
23	15.11	12.97	06.25	06.30
24	18.07	19.85	08.06	08.89
25	10.67	21.34	06.94	10.42
26	03.28	13.36	00.29	05.15
Mean	16.4	16.5	07.8	07.5
Standard deviation	09.7	06.6	05.4	03.3

colored dress. As can be seen in Table 2, 16.4% of fixations on prime colored dresses were removed due to artifacts, compared to 16.5% of fixations on non-prime colored dresses being removed. This amounted to 7.8% of the duration of all of the fixations on the prime dresses being removed, and 7.5% of the duration of fixations on the non-prime colored dresses.

D. COMPARISON OF COGNITIVE MEASURES

In the baseline period before the start of the experiment, where no motion was present, the average alpha asymmetry across all subjects was -0.57 ± 2.9 dB. Once inside the retail environment, $70.2\pm12.4\%$ of the motion free fixations on prime color dresses were longer than 100 ms, and so the EEG data kept for analysis. For fixations on non-prime color dresses $68.7\pm15.1\%$ were longer than 100 ms and so kept for analysis. In total EEG data from 8313 fixation periods were used for assessing Davidson's model of emotion for primed and non-primed color dresses. The breakdown of these between the different walls in the experiment room, and between AOIs on prime and non-prime dresses are given in Table 3.

TABLE 3. Fixation counts in the different stages of the experiment.

Participant	Prime fixations			Non-prime fixations		
	Wall 1	Wall 2	Total	Wall 1	Wall 2	Total
1	022	004	026	085	096	181
2	038	008	046	173	183	356
3	017	005	022	075	132	207
4	029	038	067	126	126	252
5	038	021	059	141	206	347
6	038	003	041	165	220	385
7	017	019	036	069	215	284
8	019	002	021	024	046	070
9	022	006	028	111	086	197
10	010	000	010	040	068	108
11	036	081	117	099	096	195
12	044	056	100	061	039	100
13	014	055	069	030	073	103
14	081	070	151	084	082	166
15	122	169	291	121	157	278
16	068	121	189	097	072	169
17	041	032	073	063	085	148
18	118	096	214	258	160	418
19	016	060	076	147	062	209
20	054	059	113	133	089	222
21	039	107	146	234	201	435
22	013	039	052	071	073	144
23	046	093	139	168	145	313
24	023	058	081	140	120	260
25	027	046	073	150	085	235
26	022	039	061	158	072	230
Total			2301			6012

Statistically significant differences in the alpha asymmetry were present between channels F3 and F4 on different sides of the head (Mann-Whitney U test, $p < 0.05$, $r = 0.027$) for EEG during the fixations on primed and non-primed dresses. This suggests an increased response effect from the color priming in the shopping task. As expected given the localized nature of alpha asymmetry, no significant differences were seen in the alpha asymmetry from EEG data in F7 and F8 (as nearby EEG locations), or P7 or P8 (as non-near locations).

Based on the dress choices of the participants, we see a clear effect of the color priming on the consumer behavior present. During the pink and the red prime conditions the pink dresses were proportionally the most popular, and during the blue prime condition none of the pink dresses were chosen.

The pink and the blue dresses were each the most popular colored dresses during the pink and blue prime conditions respectively. The relative popularity of each of the different colored dresses (0 = never chosen, 1 = always chosen) during the different prime conditions can be seen in Table 4.

TABLE 4. The standardized popularity of the dresses during different prime conditions in the experiments.

Prime condition	Colour of dress	Relative popularity
Pink prime	Pink dresses	0.17
Pink prime	Blue dresses	0.14
Pink prime	Red dresses	0.07
Blue prime	Pink dresses	0.00
Blue prime	Blue dresses	0.13
Blue prime	Red dresses	0.08
Red prime	Pink dresses	0.17
Red prime	Blue dresses	0.10
Red prime	Red dresses	0.08

IV. DISCUSSION

Non-wearable EEG measurements and non-wearable eye trackers have been combined widely previously to extract more information on human behavior than can be obtained using the EEG alone. For example [40] argued that a combined interface of EEG and eye-tracking would be a robust solution for allowing touch-less computer interaction. Reference [41] created a combined eye tracking and EEG interface, allowing eight participants to control a game using only their eye-movements, with the EEG data used to differentiate the participants' gaze between spontaneous and intentional movement.

A number of studies have investigated combined non-wearable EEG and eye tracking in consumer behavior related tasks as considered in the shopping task here [26], [42], [43]. Reference [43] analyzed consumer behavior when navigating retail websites by combining pupil dilation, the number of mouse clicks and EEG responses. However, neither [42] nor [43] were particularly successful in classifying consumer behavior using the output of their combined data. Reference [42] did not perform any combination of their eye tracking and EEG data, instead only using the eye tracking data to map transitions between choice sets and the participants' chosen objects. Reference [43] was unable to find a pattern that related to the consumers' choices using EEG, stating that this was because EEG waveforms are difficult to interpret.

Studies combining wearable EEG and wearable eye tracking, enabling free movement in environments, are much more limited. Reference [44] identified the potential of combing EEG, EOG and eye tracking recording units into a single device, with eye-movement recording intended to identify the object that the wearer wants to control, and the EEG/EOG to prompt commands in a Brain-Computer Interface. Unfortunately, due to technical shortcomings, they found that the system was not yet suitable for use. Reference [45] recognized the same technical limitations, and custom built a mobile eye tracker to combine with a wearable EEG unit. They tested their hybrid system by asking participants to complete select and press button tasks using their eye-movements, although with no subsequent analysis of the collected EEG data.

Recently several works have investigated the extraction of fixation Event Related Potentials (fERP) from EEG data co-registered with eye tracking data. For example, [46] looked at EEG during fixations while subjects viewed pictures of natural scenes, while [47] looked at fERPs while stationary with the aim of moving towards ecologically validity. However sufficiently accurate synchronization of EEG and eye tracking signals for fERP extraction is an ongoing topic of research for stationary subjects [48]. It is not yet enabled by our methodology which makes use of highly-localized time-frequency information to measure the band powers, specially the alpha band, and use them in power based analysis algorithms. We do not extract any fixation Event Related Potentials (fERP) which require much longer analysis epochs to be present. For example, [49] presented a methodology for co-registering EEG and eye tracking data for fERP extraction (in stationary subjects) where the first processing step was to remove all epochs less than 300 ms in duration. Reference [50] used a 900 ms epoch, from 100 ms before the fixation to 800 ms afterwards. Reference [47] only considered fixations greater than 500 ms in duration. Our epoch durations for analysis were approximately 250 ms on average.

In this work we have combined wearable EEG and wearable eye tracking to allow unrestricted movement of the subject for band-power based analyses, and a used a combination of eye tracking, EEG, and motion sensing to allow a highly time localized EEG analysis from only during the motion free eye fixation times. A key advantage of our methodology is that the eye tracker includes a full three axis gyroscope, as opposed to the two axis gyroscope in the EEG unit. This allows us, for the first time, to investigate which directions of movement are the most sensitive for inducing motion artifacts into the EEG trace. Reference [51] investigated the relationship between gyroscope measures of the motion and artifact manifestations in the EEG, but only using a two axis EEG gyroscope. Our results now suggest that the invocation of EEG artifacts was most sensitive to movements in the z, head rolling, direction. Both our work and [51] make use of the Emotiv Epoc EEG system as one which is widely used for mobile EEG recordings. This has flexible plastic arms rather than a cap to hold the electrodes in place, which may affect the precise artifact morphologies if similar studies are repeated using different EEG units.

Nevertheless to our knowledge this is the first demonstration of EEG band power analysis to be performed in a free movement task by using multi-modal sensing for motion robustness as opposed to artifact removal algorithms. We found that only an average of 16% of the eye fixations on dresses occurred during motion times, leaving sufficient motion free EEG epochs to analyze for alpha power changes. The percentage of fixations contaminated by motion will of course be very dependent on the task performed, and we deliberately selected a shopping task to induce a range of natural movements including walking and standing still to

look at products. In other tasks the amount of motion contamination could be higher, but we see shopping as representative natural movement task to investigate. In addition, our methodology does not preclude the use of artifact removal algorithms, which can be applied in addition to the eye fixation time localization, particularly if high channel count EEG units are employed.

Within our natural movement shopping task our results have shown an increased frontal asymmetry when comparing primed color and non-primed color dresses in a retail environment. Reference [52] used EEG to compare participant responses to clothing apparel products of various levels of attractiveness, viewing them on a computer screen in a lab based experiment. Using Davidson's model of emotion, [52] identified significantly different responses between participants looking at attractive and unattractive apparel garments and noted there is a lack of consumer neuroscience research focused on clothing. Consumer behavior is often influenced by the individual's environment, and priming is routinely used in practice to influence consumer behavior [53], [54]. Due to the subconscious nature of priming, participants are often unable to accurately recall their influences [55]. This highly motivates the use of EEG and other bio-metric measures to observe consumer responses effectively, and our multi-modal sensing approach can help allow this in a range of natural movement situations where it has not previously been possible.

V. CONCLUSIONS

Hardware for wearable EEG recording has recently become available, but still suffers from the presence of motion artifacts when subjects move in an unconstrained way. This paper has presented a new method for using multi-modal motion sensing to combine the information from a wearable EEG unit with that from a wearable eye tracker to allow only the EEG during fixations on a wanted area of interest to be analyzed. This has provided two contributions. Firstly, during free motion movements by a subject, our synchronization approach allows a highly time localized analysis such that although the EEG contains many motion artifacts in general in all cases more than 65% of the wanted EEG during motion was artifact free and could be analyzed. It also shows that, for our Emotiv EEG unit, head movements in nodding and rolling motions have statistically significantly lower thresholds for motion artifact induction than the head shaking direction. Secondly, we have used our new methodology in an EEG priming task, altering the color of the mannequin's garments and the environment as subjects move around a simulated shop. This has demonstrated differences in EEG frontal asymmetry can be measured between when subjects are looking at prime and non-prime colored dresses, and gives a new tool for the analysis of consumer behavior.

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