CEREBRE: A Novel Method for Very High Accuracy Event-Related Potential Biometric Identification

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Abstract—The vast majority of existing work on brain biometrics has been conducted on the ongoing electroencephalogram. Here, we argue that the averaged event-related potential (ERP) may provide the potential for more accurate biometric identification, as its elicitation allows for some control over the cognitive state of the user to be obtained through the design of the challenge protocol. We describe the Cognitive Event-RElated Biometric REcognition (CEREBRE) protocol, an ERP biometric protocol designed to elicit individually unique responses from multiple functional brain systems (e.g., the primary visual, facial recognition, and gustatory/appetitive systems). Results indicate that there are multiple configurations of data collected with the CEREBRE protocol that all allow 100% identification accuracy in a pool of 50 users. We take this result as the evidence that ERP biometrics are a feasible method of user identification and worthy of further research.

Index Terms—Biometrics, emergent biometrics, biometric protocols, performance and evaluation.

I. INTRODUCTION

BRAIN biometrics potentially have many advantages over current conventional biometrics, such as fingerprints and retinal scans. For example, fingerprints can be surreptitiously duplicated via high resolution photography, as was demonstrated in a recent high-profile incident where German Defense Minister Ursula von der Leyen's fingerprints were copied without her knowledge by a member of the Chaos Computer Club,

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who took a high resolution photograph of her hands at a press conference [1]. Brain activity, in contrast, cannot be measured without a person's knowledge with current technology, which requires too much proximity and is too bulky to be used covertly. As another example, in order to provide a brain biometric, a user must be alive– indeed, the lack of active brain activity, as measured by the electroencephalogram (EEG) is one clinical indicator that a person is brain dead [2]. This characteristic suggests that brain biometrics might not only protect the system, but also the users of that system. As a third example, many features of the EEG (and the stimulus-locked and averaged Event-Related Potential, ERP, which will be utilized here) are non-volitional, meaning that they are not under the control or conscious apprehension of the user, which further means that a user cannot (willingly or unwillingly) divulge their contents [3].

Despite these advantages, brain biometrics are not currently widespread in practical applications— indeed, they are referred to as "esoteric" in textbook usage [4]. One reason for this is that 100% identification accuracy has been difficult to attain with brain biometrics. One report has reached this benchmark [5], but is is much more common to see slightly less accurate results (c.f. 97% identification accuracy in [6]; 98% in [7], 96.6% in [8], 96% in [9]).[1] In prior work, we argued that one reason for this is that most past attempts at brain biometric identification have utilized the EEG as the biometric measure (For example [9]–[12]; but see also [13]), instead of the ERP (but see [14], for an important exception). The EEG in humans is an ongoing, continuous signal that can be collected in the absence of any particular stimulation. While this makes it convenient to collect, the fact that it is collected in the absence of stimulation means that the mental states of the user are under no experimental control during its collection. Thus, two users ostensibly undergoing the same biometric enrollment and challenge protocol might actually be in very different cognitive states, both from each other and across acquisition sessions, making the classifier's task much more difficult. Additionally, because the EEG is often analyzed in the frequency domain for biometric use, it's temporal resolution is extremely poor. And, because the EEG

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[1]Of course, there are other concerns besides reaching the 100% accuracy benchmark that contribute to a lack of applied use for brain biometrics. These include the expense of appropriate bioamplifiers and sensors, and the expertise required to acquire satisfactory data. However, there is little point in addressing these more applied issues if it has not been demonstrated that, with the best equipment and with expert users, it is in fact possible to acquire a unique brain biometric. This demonstration is what we seek to provide here.
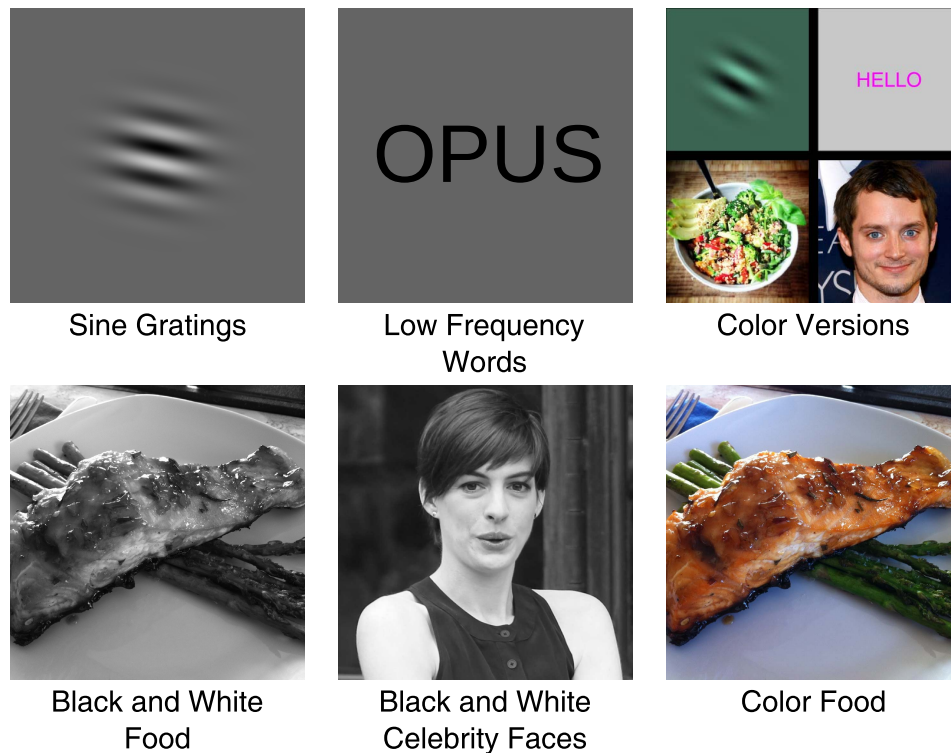
Fig. 1. Examples of each type of stimulus used in the CEREBRE protocol: sine gratings, low frequency words, color versions of black and white images, black and white foods, black and white celebrity faces, and color foods. For the foods and celebrity faces, 10 tokens of each type (e.g., 10 different types of salmon, 10 different Anne Hathaways) were obtained from Google Images.

is not collected time-locked to any type of stimulation, it does not and cannot reflect the same narrow, specific, cognitive processes that can be captured by the stimulus-time-locked ERP signal. The EEG is thus more reflective of the basal state of the user (e.g., their level of stress or arousal; see, for example, [15]) than of any specific cognitive process, as cognitive processes unfold in the brain in a time frame on the order of only a few milliseconds (e.g., [16]).

The ERP, in contrast, is a stimulus-averaged signal time-locked to the presentation of some event of interest. When ERPs are created through averaging over many trials of a particular type of event, brain activity not related to the event of interest is reduced and brain activity related only to the event of interest is emphasized (especially that reflecting excitatory post-synaptic potentials in the pyramidal cells of the cortex; find review of the source and nature of the ERP in [17]). This allows the experimenter to tightly control the cognitive state of the user being reflected in the resultant ERP activity. This is not possible with the raw EEG signal, because the EEG is not collected time-locked to stimulation, that is, it is not possible to isolate, for example, face processing or visual processing within the EEG signal. This is especially true when EEG is analyzed in the frequency domain, which requires a a time series of data orders of magnitude longer than the millisecond time frame over which cognitive processes unfold. This is a disadvantage, because when the cognitive state of the user is known, it can be directed, through stimulation, to states that are likely to differ in unique ways across individuals. Here, we will report the results of an ERP biometric protocol that does this, by using categories of stimulation that are likely to cause unique patterns of functional brain activity across users. This work represents an important advance in brain biometric protocols, in that it has been designed with control over the cognitive state of the user explicitly in mind (c.f. [11], [18]–[20]).

We hypothesized that, by controlling the cognitive state of users through specific modes of stimulation likely to produce differential responses across participants, especially when multiple modes are combined, we would be able to achieve higher biometric identification accuracy than has been achieved in the past by protocols that do not control the cognitive state of the user or that do not combine multiple modes of stimulation. We designed the CEREBRE protocol to test this hypothesis. What we hope this protocol will add to the literature is an example of the utility of providing precise, multi-modal stimulation to participants, to precisely control their cognitive states and draw from multiple functional brain networks, during biometric data collection. This work extends previous work with ERP biometrics ([13], [14]) by including multiple modes of stimulation, which we predict will result in more identifiable responses when combined.

II. THE CEREBRE PROTOCOL

Here, we will attempt biometric classification based on ERP responses to 5 categories of stimulation likely to each elicit distinct patterns of activation across individuals, and we will compare biometric identification accuracy from this data to biometric identification accuracy obtained from (1) a more standard eyes-closed EEG acquisition protocol and (2) a pass-thought protocol [21], [22]. The categories of stimulation used for the formation of ERPs were as follows; examples

of all categories of stimulation are available in Figure 1. (1) Sine gratings. Sine gratings were selected because they are known to strongly stimulate the primary visual cortex (e.g., [23]), which, in turn is known to vary in its topographical pattern of folds from person to person (e.g., [24]). Sine gratings elicit robust visual potentials over the back of the head (e.g., [25]; review in [26]). (2) Low frequency words. Low frequency words were selected because it is well established in the psychophysiology literature that the ERP response to words that an individual knows the meaning of differ from the response to words that that individual does not know the meaning of, and that, further, individuals exhibit substantial variation in their knowledge of low frequency words (e.g., [27]). The word frequency effect more generally on the ERP is well-characterized as a greater negativity for low than high frequency words beginning around 250 ms post-stimulus onset over the back of the head [16], [28]. In fact, variability in individuals' response to wordforms was the basis of our previous work with brain biometrics, which achieved 97% identification accuracy [6]. (3) Images of foods. Images of foods were selected based on the intuition that food preference is highly individual. This intuition is accompanied by at least one result demonstrating that structures in the ventral midbrain exhibit activation profiles in response to images of food that vary proportionally to individuals preferences for those foods [29]. The ERP response to food stimuli is well characterized (e.g., [30], [31]) (4) Celebrity Faces. Celebrity faces were selected based on the observation that celebrities can be polarizing, with celebrities that some individuals love being hated by other individuals and vice versa. The possibility of a neural substrate for this type of preference is at least partially supported by results suggesting that structures in the orbitofrontal cortex exhibit activation profiles in response to images of faces that vary proportionally to an individual's judgment of those faces' attractiveness [32]. Face stimuli robustly elicit an occipital negativity peaking around 170 ms in the ERP (see [33], for review). (5) Oddball stimuli. When participants are asked to respond to a rare (oddball) target stimulus embedded in a sequence of more common stimuli (e.g., an X in a sequence of Os), a large, distinct response potential known as the P300 is elicited (review in [34]). The morphology of the P300 is known to exhibit individual variation, with some results suggesting that P300 latency is correlated with general intelligence (e.g., [35]). Indeed, the P300 has been used as a basis for the relatively limited work that has been done with ERP biometrics in the past [13]. Here, oddball stimuli consisted of images from the other four categories (that is, sine gratings, low frequency words, foods, and faces), presented in color, instead of black and white. Twenty-five percent of images in the protocol were randomly selected for each participant to be presented in color (more details in Methods, below). Participants were asked to respond with a button press whenever they detected a color stimulus. Overall, and as we have just reviewed, each of the types of stimulation included in the CEREBRE protocol not only strongly and unequivocally impact the ERP, but also are likely to elicit individually variable patterns of brain activity.

For example, it is unlikely that any two individuals will have exactly the same food preferences. Further, it is even less likely that two individuals will have identical responses across multiple categories. For example, it is less likely that two individuals will have exactly the same food preferences AND exactly the same vocabularies than that they will have exactly the same food preferences, and it is even less likely that two individuals will have exactly the same food preferences, exactly the same vocabularies, and exactly the same pattern of cortical folding in the primary visual cortex, and so on. We therefore predict that, while ERPs elicited in response to single categories of stimulation (e.g., foods) will be somewhat identifiable, combinations of ERPs elicited in response to multiple categories of stimulation will be even more identifiable. This prediction is supported by the likelihood that each category of stimulation will draw upon differing (though overlapping) brain systems. For example, if the sine gratings call primarily upon the primary visual cortex, and the foods call primarily on the ventral midbrain, then considering both responses together for biometric identification provides multiple, independent, pieces of information about the user's functional brain organization– each of which can contribute unique variability to the overall biometric solution.

III. METHODS

A. Participants

A total of 56 individuals, ranging in age from 18 to 43 years old, participated (37 female, mean age 20.2, 16 subjects were 18, 15 subjects were 19, 14 subjects were 20, 6 subjects were 21, 1 subject was 22, 1 subject was 23, 3 subjects were 28 and 1 subject was 43). 6 participants were excluded due to failure to follow instructions or equipment failure. The final database of 50 participants is substantially larger than the reported mean of 29 across 10 brain biometric studies reviewed in [36]. No particular screening was performed on these participants, as the goal of a biometric is to be as broadly applicable (universal) as possible. Indeed, the age range of our participants is wider than what might be typical in even a very large a cognitive ERP study (e.g., [37]), however, of course, if brain biometrics are to ever enter applied use, they must be accurate across a wide age range, and the only way to demonstrate that this is the case is by testing brain biometric protocols across a wide age range, as we have done here. Participants were compensated with either course credit or money. The Internal Review Board of Binghamton University approved the experimental protocol.

B. Materials

During ERP data collection, participants were exposed to 400 images: 100 sine gratings, 100 low frequency words, 100 images of foods, and 100 celebrity faces. 300 of the 400 were presented in black and white, and a different random 100 for each participant were selected, without replacement, and presented in color— these 100 color images were therefore the oddball stimuli, since they were rare, unpredictable, and required a response (i.e., we asked participants to respond with a button press when they detected a color stimulus). Examples of all stimulus types

are available in Figure 1. All stimuli were cropped to a uniform 500×500 pixels. Composition of each category of stimulus was as follows. The 100 sine gratings were randomly generated for each participant, using the following parameters: orientation of the grating was allowed to vary across the full 360 degrees; number of pixels per period of the visible sine wave was randomly selected between 1 and 80; sine gratings created in this manner were then multiplied by a Gaussian kernel where one standard deviation of the Gaussian covered a random number of periods of the sine wave. Resultant sine gratings were centered on a 500×500 pixel uniform grey background. To create color versions of the sine gratings to serve as color targets, a color mask with a random, but high saturated, color was overlain. Low frequency words were drawn from the GRE (Graduate Record Exam) with the constraint that they have less than 10 letters. Words were then printed in black Arial font centered on a uniform 500×500 grey background. To create color versions of the word stimuli to serve as color targets, the color of the font was selected randomly in the high saturated half of the spectrum. To select foods, we first completed a norming study where 44 participants (who did not take part in the ERP study) were asked to list 10 foods that they LOVE and 10 foods that they HATE. From the pool of responses, the 10 most bipolar foods were selected, that is, the 10 foods that were listed the most times in both LOVE and HATE were selected. Then, 10 instances of each of these 10 foods (for a total of 100 images) were sought from Google Images; 100 desaturated (black and white) copies were also created. To select celebrity faces, we again asked the same pool of 44 participants that performed the food norming to also list 10 celebrities that they LOVE and 10 celebrities that they HATE. Once again, the 10 most bipolar celebrities were selected, and 10 instances (for a total of 100) were sought from Google Images. Once again, 100 desaturated copies were also created. During portions of data collection where participants were asked to think of a pass-thought (details below), a black key icon was presented on the same 500×500 pixel grey background.

C. Procedure

Prior to data collection, participants were asked to select a "pass-thought". Participants were given 5 pre-selected options (e.g., "Your favorite birthday", "Your grandma's face") and were also given the option to select their own pass-thought, in which case they were asked to write down that self-selected pass-thought. Participants were asked to choose a pass-thought that they could remember strongly. After selecting their pass-thought, participants were shown the black key icon that was meant to cue the pass-thought and were instructed to think about their pass-thought every time that key was presented during the experiment.

During data collection, participants were seated in an electrically shielded, sound-attenuated booth and positioned 75 cm away from a 24 inch LCD computer monitor with a resolution of 1920×1080, a black-to-white response rate of 1 ms and a refresh rate of 60 Hz. Before the experiment, participants

were allowed to watch their EEG to see what it looks like, and were given a brief biofeedback demonstration, where they watched the EEG record change when they blinked and moved their eyes, and tensed the muscles in their face and shoulders. Participants were then told: "you can see how eye movements and muscle tension can impact your brain waves, for this reason, we ask that you remain as still as possible and refrain from blinking and moving your eyes except during particular parts of the experiment." This type of demonstration is known to improve signal quality (see [38]), by substantially reducing ocular and EMG artifacts. Participants were then given a short demonstration of trial structure, including explanation of when it was and was not acceptable to blink or move the eyes, and informed that their task was to watch the stream of images for color images and to press a button on a response pad as fast as possible with a finger on their right hand when they saw a color image. Participants were told that they did not have to make any response to non-color images, with the exception that, when the black key icon appeared, they were to think of their pass-thought. Following this demonstration/explanation, the 400 images were presented in a random order to each participant. The 400 images were broken into 4 blocks of 100 images each, and participants were given breaks between blocks. The pass-thought icon was presented for 3 seconds at the beginning and end of each block. After the initial presentation of the 400 images, participants were then shown 90 randomly selected color foods– this was done because pilot work indicated that foods presented in black and white were not nearly as appetizing as foods presented in color. During this block, the target stimulus was a color image of a hamburger; participants were asked to respond every time they saw that particular hamburger, which was presented 10 times. The pass-thought icon was also presented for 3 seconds at the beginning and end of the color foods sequence, meaning that the pass-thought was cued for 3 seconds 10 times across the experiment, for a total of 30 seconds. Finally, participants were asked to close their eyes and relax but not fall asleep for 5 minutes, in order to acquire resting-state EEG. The total duration of the experiment was approximately 1.5 hours, including 0.5 hour for electrode placement and variable time in the breaks between blocks. Each block lasted approximately 5 minutes and there were 6 blocks in total.

Trial structure is presented in Figure 2. The experiment was not self-paced (that is, each trial ended and the next one began automatically, regardless of whether a participant made a response or not), though the automatic pace was selected to be comfortable and not particularly challenging for participants.

D. EEG Recording

The EEG was recorded from 26 active Ag/AgCl ring electrodes placed in an elastic EasyCap with a geodesic arrangement. The electrooculogram (EOG) was recorded using two electrodes placed on the outer canthi of the left and right eyes to monitor for horizontal eye movements; a third EOG electrode was placed on the sub-orbital ridge of the left eye to monitor for vertical eye movements and blinks. Online, the EEG and EOG were referenced to the left mastoid, offline,

Fig. 2. Example of the trial structure used in the CEREBRE protocol. Each stimulus is preceded and followed by a black fixation cross. Participants are asked to keep their eyes as stationary on this cross as possible, to reduce ocular artifacts. The presentation duration of the fixation cross at the start of each trial is jittered around a mean of 500 ms to reduce the buildup of anticipatory potentials. At the end of each trial, the fixation cross turns white– participants are informed that they should do their best to blink and move their eyes only when the white fixation cross is on the screen.

they were re-referenced to the average of the left and right mastoid. Thus the total number of sensors was 30: 26 on the scalp, 3 on the face, and the right mastoid. Inter-electrode impedances were kept below 50 KΩ [39]. EEG and EOG were recorded with a Brain Vision Brain Amp DC with a low pass filter at 250 Hz and a high pass filter with a 10 s time constant, and sampled at a rate of 500 Hz with an A/D resolution of 16 bits. No artifact rejection was applied, though baseline correction to a mean of 0 was applied to each individual trial. ERPs were formed for each type of stimulus (e.g., words, celebrity faces) at each electrode time-locked to stimulus onset. Each ERP included 550 samples, 50 pre-stimulus and 500 post stimulus, resulting in an 1100 ms ERP; Averaged ERPs were once again baselined to the mean of the 100 ms pre-stimulus interval. ERPs were filtered with a band-pass of 1-55 Hz for classification. This differs from what might often be observed in the ERP literature, where ERPs of the type acquired here are often filtered below 20 Hz for measurement (e.g., [16], [27], [37]). We chose not to heavily filter this data in order to leave the cognitive gamma band intact [40]. However, given that filtering to a lower frequency is also common in the ERP literature (e.g., in order to reduce the impact of muscle activity in the ERP record [41]), we also investigated several classifiers where data were filtered between 1 and 20 Hz (though see also [42] on the dangers of over-filtering). In what follows, results are reported from data filtered to 55 Hz unless otherwise noted.

E. Classification

A simple discriminant function based on normalized cross-correlation was used for classification. This classifier was selected on the basis of our previous work with ERP biometrics, where we investigated the efficacy of several classifiers, including SVM and several neural network approaches [6]. That work demonstrated that the cross-correlator was more accurate than any other single classifier, including SVM. Additionally, the cross-correlator is computationally more lightweight than classifiers that require training. For these reasons, the cross-correlator is the only classifier that will be used here.

For classification, each participant's responses to each type of stimulus were split into two randomly composed halves: a reference half and a challenge half. For example, of a participant's 90 responses to colored foods, 45 randomly selected responses were averaged into a reference ERP and the remaining 45 were averaged into a challenge ERP. Thus, there was a reference ERP and challenge ERP from each participant for each type of stimulus. Figure 3 displays reference and challenge ERPs for two representative participants from the black and white foods – note that, even visually, it is evident which of the challenge ERPs corresponds to which of the reference ERPs. Initially, only data from a middle occipital channel (MiOc, that used in our prior work) were included; later, in the voting classifiers (described below), data from more electrodes were included. The middle occipital channel was selected on the basis of previous work that indicated that especially high identification accuracy is possible from data collected over this site ([6]). This is perhaps unsurprising, as it is well established that occipital electrodes capture activity in the human primary visual cortex (e.g., [33]) and the method of stimulation employed here and in the related, prior, work was visual.

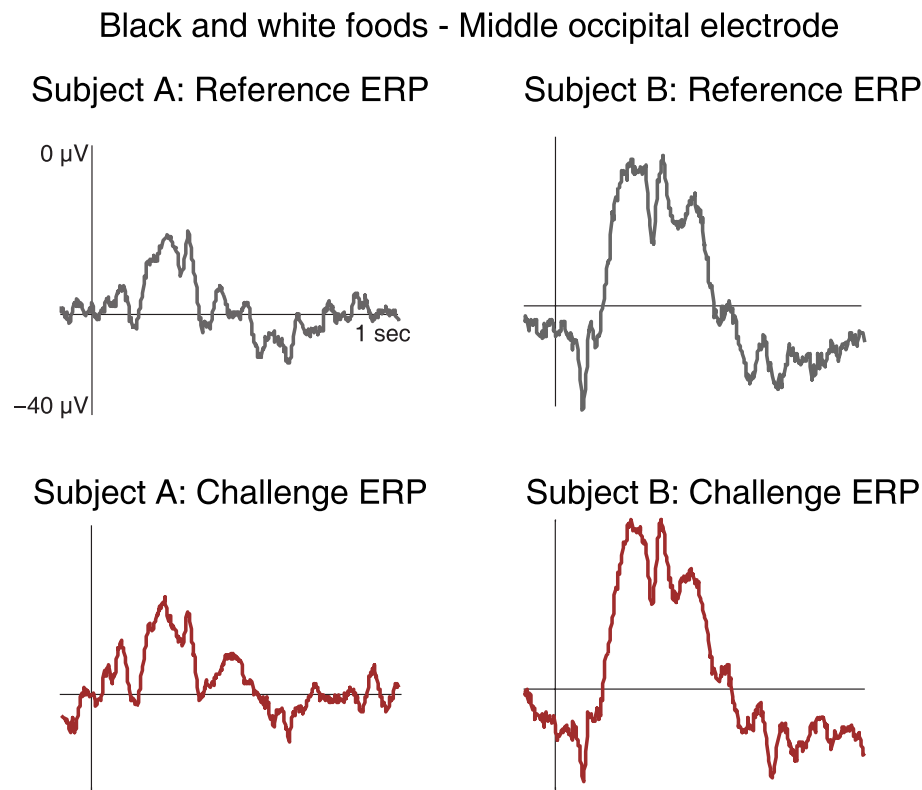## Black and white foods - Middle occipital electrode

Fig. 3. Reference and challenge ERPs from two representative participants in response to black and white foods over the middle occipital (Oz) channel. Notice that, even by eye, it is possible to determine which challenge ERP corresponds to which reference ERP.

The classifier's goal was, given a challenge ERP elicited by a particular type of stimulus, to identify, via cross-correlation, which reference ERP was most similar, thus providing an identification of that challenge ERP. For each stimulus type, each participant's challenge ERP was cross-correlated with their own reference ERP (self-self) and with the reference ERP of the 49 other participants also in the system (self-other). The maximum rectified, normalized, value returned by the cross-correlation was taken as a single-value similarity index ranging in [0,1]. The classifier's guess as to which reference the challenge ERP corresponds to is the reference with the highest similarity index with the challenge ERP. This method will be successful if a participant's self-self cross-correlation is larger than any self-other cross-correlation. Note that this procedure is an identification classifier, in that the classifier must compare the challenge with all references. This provides a $1/50 = 2\%$ chance that the classifier will correctly identify a challenge. This is in contrast to a verification classifier, where the classifier only has to compare the challenge with a single reference, which provides a $1/2 = 50\%$ chance that the classifier will correctly verify the challenger's identity. Identification, as implemented here, is thus a more difficult classification problem than verification.

Each ERP consisted of 550 samples (1100 ms of data sampled at 500 Hz); the full ERP time series was submitted for classification without feature extraction. This differs from previous brain biometric approaches, which heavily rely on feature extraction (review in [36]). We chose not to perform any feature extraction here for several reasons. First, even without feature extraction, the cross-correlator is very lightweight, as it does not require training. Second, our prior work is highly suggestive that even this simple classifier, fed the full ERP time series, can perform very well [6]. Third, ERP biometrics are still relatively understudied, meaning that it is not entirely clear what the appropriate features for extraction might be. That is, there are numerous potential features of the ERP that might be individuating, for example, difference amplitude of the P3 [14], peak-to-peak amplitude or peak latency of the visual evoked potentials [43], and the time derivative of the raw ERP [14].

The single-channel, single-stimulus type classifiers are computationally very lightweight, and also only require data from 1 active electrode sensor. However, these classifiers do not maximally take advantage of the unique variance across electrode channels and stimulus types [6]. For that reason, we also constructed several voting classifiers, wherein multiple channels and/or multiple stimulus types were allowed to "vote" on the identification of the challenge ERP. More details on these are provided in the Results, below.

IV. RESULTS

Figure 4 presents the mean identification accuracy for all stimulus types and for the pass-thought and resting state EEG in data filtered below 55 Hz. In data filtered below 20 Hz, classification accuracies were slightly higher (Sine gratings: 60%, Words: 78%, Black and white celebrities: 82%,
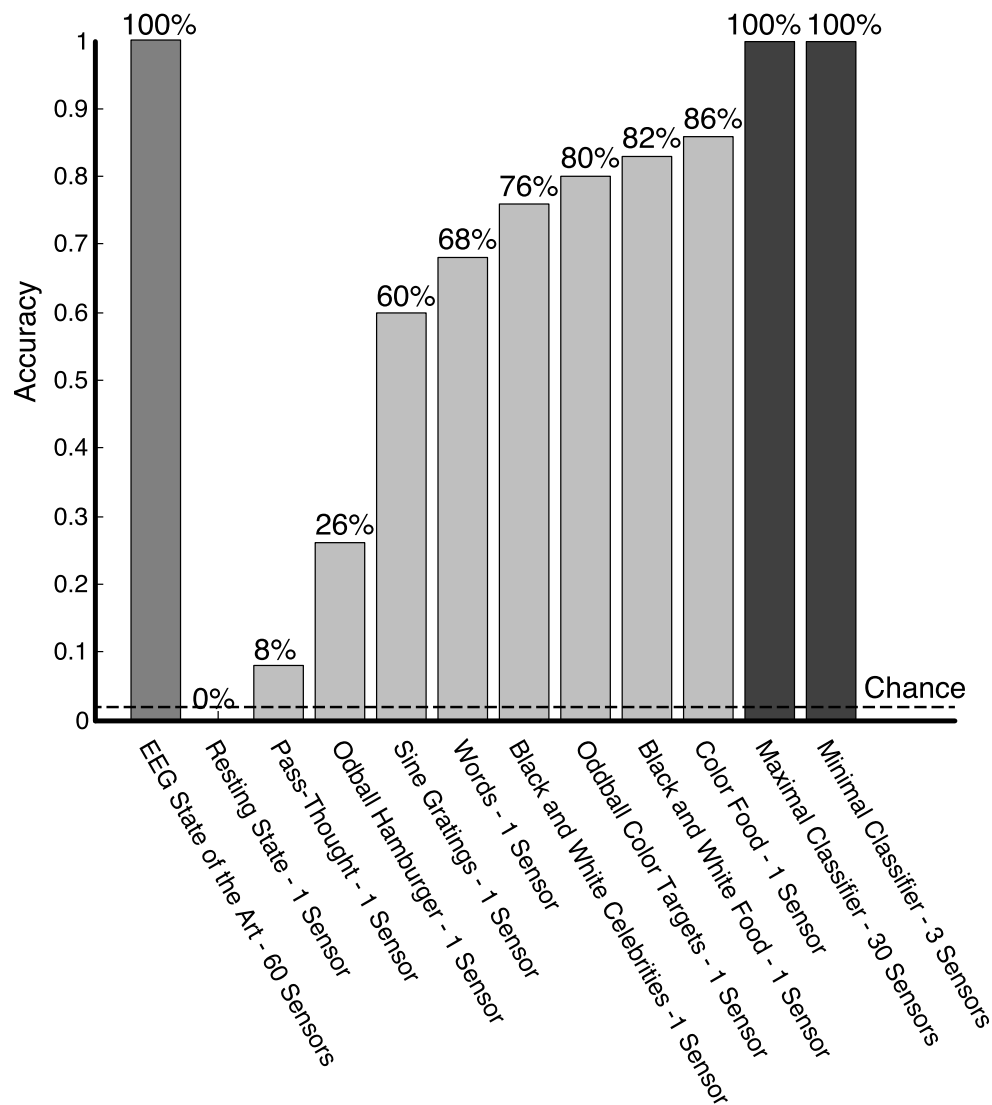
Fig. 4. Identification accuracy for the state of the art in EEG biometrics [5], resting state EEG, pass-thought, single stimulus type single channel classifiers, and the "maximal" and "minimal" voting classifiers that provided 100% identification accuracy. Chance identification accuracy is 2%; all classifiers exceeded chance except for the resting state EEG classifier. For all the single sensor categories shown here, the results correspond to the sensor placed over the middle occipital scalp.

Oddball color targets: 84%, Black and white food: 90% and Color food: 84%). All stimulus types achieved a greater than chance identification accuracy, although the resting state EEG did not (0%)— however, many prior reports have achieved much higher identification accuracy with EEG, so, for reference, Figure 4 also displays field-leading 100% accuracy from La Rocca et al. (2014) [5]. It is likely that one reason the EEG classifier performed poorly here is that no feature extraction was performed prior to classification. We made this choice deliberately, wanting to perform a fair comparison where the same analytic techniques were applied to both EEG and ERP. The food (black and white and color), oddball target, celebrity, word, and sine grating classifiers each included at least 30 trials in both challenge and reference ERPs. The hamburger and pass-thought classifiers, in contrast, only included 5 trials in challenge and reference ERPs. Thus, while it is not valid to compare the hamburger or pass-thought classifiers to the others

(because they included less data), they can be compared to each other. And, even when the pass-though is compared to a classifier including an equally small number of trials, the pass-thought is a relatively inaccurate means of classification. The highest single-channel, single-stimulus type classifier accuracy was 86% for the color foods over the middle occipital scalp. Indeed, the majority of channels with the highest classification accuracy were found over the back of the scalp (posterior channels), with the middle occipital (MiOc) channel being highly accurate in general; this is consistent with our prior work [6]. Appendix A.1 provides the locations and names of all electrode sites; Appendix A.2 displays classification accuracy over the entire scalp for all 6 single-item classifiers.

After analyzing the single-channel, single-stimulus type classifiers, we sought to determine whether classifier accuracy could be improved by allowing multiple channels and/or stimulus types to vote on identification. This analysis was
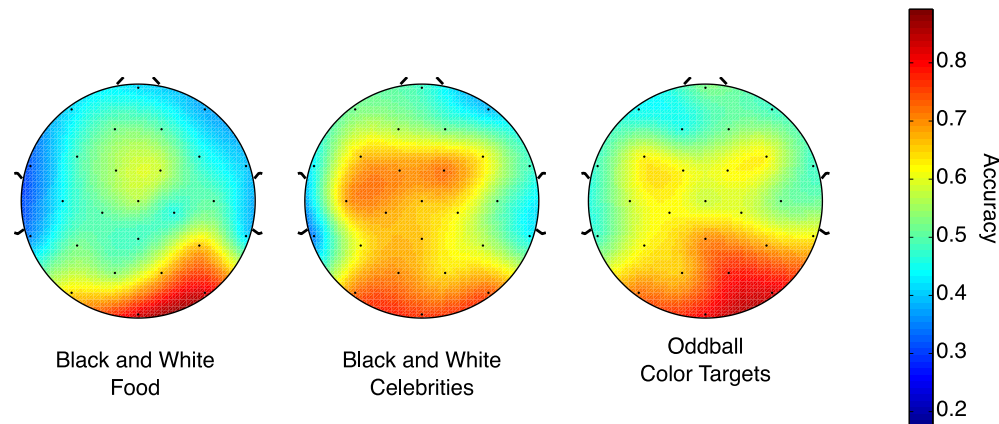
Fig. 5. Grand averaged topographic map of identification accuracy for the black and white food, black and white celebrities, and oddball color targets classifiers, with areas of the scalp providing more accurate classifications in warm colors and areas providing less accurate classifications in cool colors. As expected, the oddball color targets classifier was most accurate over a broad region starting on the back of the head, which is in accordance with the distribution of the P300 component. The black and white food classifier, in contrast, is most accurate over more occipital part of the head. The celebrity classifier, meanwhile, is most accurate over an intermediate region of scalp. These distinct topographies suggest that these three classifiers draw on separable functional brain networks.

based on the fact that, by design, the different stimulus types likely tap into different functional brain networks, each one contributing unique variability to a user's full set of ERP responses. Figure 5 illustrates this concept, by displaying scalp maps of classification accuracy for the black and white food, celebrity, and oddball color targets classifiers. As would be expected, maximum classification accuracy for the oddball color targets is found a broad area originating on the back of the head, which is in accordance to the distribution of the P300 component. The black and white food, in contrast, are best classified over the most occipital part of the head. Celebrities are best classified over a group of channels intermediate between the oddball and food areas of best classification. Thus, the regions of scalp that provide strong single-stimulus type classification accuracy differ across stimulus types, which suggests that combining information from multiple stimulus types and/or channels might improve classifier accuracy.

We started our investigation of multi-stimulus, multi-channel classifiers by including votes from all 30 channels and all 6 stimulus types (for a total of 180 votes per challenge ERP). This classifier achieved 100% identification accuracy. However, even though this "maximal" classifier is perfectly accurate, it is the least practical classifier from an applied standpoint, as it requires the most data collection (i.e., collection of responses to 6 stimulus types) and the most preparation time (to prepare a full electrode montage for data acquisition). Therefore, we next sought to determine whether 100% identification accuracy could still be obtained with fewer channels and/or stimulus types. There were many combinations of channels and stimulus types that allowed 100% identification accuracy, indicating that, overall, this protocol is robust. The "minimal" classifier that still allowed 100% identification accuracy included votes from 4 single-item type classifiers (Black and white celebrities, Oddball color targets, Color food and Words) over 3 electrodes, located over the left middle occipital (LMOc), right middle occipital (RMOc) and middle occipital (MiOc) channels. As mentioned above,

MiOc is the same channel identified as highly accurate in our prior work, [6]. In data filtered to 20 Hz, the minimal perfect accuracy classifier was slightly larger, requiring votes from 4 single-item type classifiers (Black and white foods, Black and white celebrities, Oddball color targets and Color food) over 4 electrodes (left middle occipital (LMOc), right middle occipital (RMOc), right lateral occipital (RLOc) and middle occipital (MiOc) channel). Thus, while data filtered to 20 Hz enable slightly more accurate classification in single-item type classifiers, the minimal perfect identification accuracy classifier they enable is larger than that enabled by the 55 Hz low pass filtered data.

In addition to reducing the number of sensors and stimulus categories included in the classifier, another way to reduce the time needed for identification by this protocol would be to reduce the number of trials included in the challenge. To this end, for both the maximal (all channels, all categories) and minimal (3 channels, 4 categories) classifiers that provided 100% identification accuracy, we examined the relationship between number of trials included in the challenge and classifier accuracy. Approximate random sampling was used, where 25 different randomly selected subsets of trials were analyzed for each number of trials included (i.e., 25 different random selections of 2 out of 30 trials, 25 different random selections of 3 out of 30 trials, etc.) in order to reduce variability in the estimate of accuracy at each number of trials due to which trials were selected. The minimum number of trials needed in the challenge to produce 100% identification accuracy was 27 trials (=27 seconds) for the maximal classifier. The minimal classifier did not reach 100% accuracy unless all available trials were used.

The minimal classifier performs better than any single-channel, single-category classifier, however, it is not clear whether this is actually because it is advantageous to combine information from multiple brain networks (as probed by the different categories of stimulation), or simply because the minimal classifier includes more data than any of the

TABLE I

FOUR TYPES OF VOTING SCHEME: (1a) A SCHEME THAT INCLUDES 6 VOTES: ONE FROM EACH TYPE OF STIMULATION AT A SINGLE ELECTRODE, (1b) A SET OF SCHEMES THAT INCLUDE 6 VOTES: NAMELY A VOTE FROM EACH OF THE TOP SIX ELECTRODES IN EACH CATEGORY OF STIMULATION, (2a) A SCHEME THAT INCLUDES 24 VOTES: VOTES FROM THE BEST 4 ELECTRODES FOR EACH CATEGORY, AND (2b) A SET OF SCHEMES THAT INCLUDES 24 VOTES: ONE VOTE FROM EACH OF THE 24 SCALP ELECTRODES WITHIN EACH CATEGORY OF STIMULATION. NOTE THAT, ON AVERAGE, COMBINING DATA ACROSS STIMULUS TYPES, AS IS DONE IN THE A TYPE CLASSIFIERS IS MORE ACCURATE THAN COMBINING DATA CROSS CHANNELS, AS IS DONE IN THE B TYPE CLASSIFIERS

6 Votes	Accuracy	24 Votes	Accuracy
1a: 6 Categories/ MiOC	**0.92**	2a: 6 cat/ top 4 electrodes	**1**
1b.1: 6 electrodes/Celebrities	0.86	2b.1: 24 electrodes/Celebrities	0.86
1b.2: 6 electrodes/Black and White Food	0.9	2b.2: 24 electrodes/Black and White Food	0.76
1b.3: 6 electrodes/Words	0.8	2b.3: 24 electrodes/Words	0.9
1b. 4: 6 electrodes/Oddball Color Targets	0.88	2b.4: 24 electrodes/Color Targets	0.86
1b.5: 6 electrodes/Color Food	0.9	2b.5: 24 electrodes/Color Food	0.9
1b.6: 6 electrodes/Sine Gratings	0.54	2b.6: 24 electrodes/Sine Gratings	0.58
1b Mean	**0.81**	**2b Mean**	**0.81**

single classifiers. In order to know whether it is truly advantageous to combine data elicited in response to multiple stimulus types, it is necessary to compare voting classifiers that all have the same number of voters, but vary in how many categories of stimulation are included. We therefore examined the performance of two additional sets of voting classifiers: 1) a set of classifiers that all include 6 votes— one including a single vote from each of the 6 types of stimulation (6 voters), and another 6 that include a vote from each of the best 6 electrodes within a single type of stimulation (6 voters each). 2) A set of classifiers that all include 24 votes— one including votes from the best 4 electrodes from each of the 6 types of stimulation (24 votes) and another 6 including one vote from 24 scalp sensors within each single category of stimulation (24 votes). What these schemes allow us to examine is whether combining categories or combining channels improves classification more. We would expect that combining categories would be more effective, based on our hypothesis that combining the activity of multiple functional brain networks is what gives this protocol its power. Table I displays the results of these voting schemes. As expected, it is, on average, more effective to combine categories of stimulation than to combine sensors, even when the number of voters is kept constant.

Note that, because activity at nearby electrodes must be correlated due to volume conduction, it is not necessarily the case that activity across responses to different stimulus categories be correlated. This means that combining electrodes may result in less ERPs with less information content than combining stimulus types. This would further mean that in the voting scheme we just described the multi-electrode voters may perform more poorly than the multi-stimulus-category voters not because combining stimulus types is more advantageous than not combining stimulus types, but because combining stimulus types is only more advantageous than combining electrodes. To address this possibility, we constructed another set of voters, each including 3 votes. The 3 votes could either be 3 ERPs constructed of 10 trials from the same

stimulus type (e.g., 3 10 trial ERPs all constructed from foods) or 3 ERPs of the same size constructed from 3 different stimulus types (e.g., a 10 trial color food ERP, a 10 trial black and white food ERP and a 10 trial oddball ERP). Results were inconclusive– breaking apart the data into ERPs this small resulted in comparably poor identification performance for all voting schemes (for combining 3 same type ERPs: 26.5% accuracy, for combining 3 different type ERPs: 27.2% accuracy). From this we conclude that in order to better examine whether combining stimulus types is more effective than simply collecting many times more single-stimulus-type data, a larger dataset than that acquired here would be needed. However, even if it is the case that 100% identification accuracy can be obtained with single stimulus-type classifiers, what our analysis of that type of classifier shows here is that such a classifier would have to have many more trials than we collected, which would make the protocol substantially less useful for applied use.

V. DISCUSSION

We set out to examine the extent to which Event-Related Potentials (ERPs) might allow for more accurate biometric identification than other commonly used brain biometric measures, such as the EEG or "pass-thought" type approaches. We noted that ERPs, when compared especially with EEG, provide some measure of control over the cognitive state of the user, and also can be elicited in response to different forms of stimulation that are, each, likely to produce individual variation. We hypothesized that these factors might allow for highly accurate ERP biometric identification. We therefore designed the CEREBRE protocol, wherein participants were asked to view several categories of stimuli each likely to produce variable responses across participants (sine gratings, low frequency words, celebrities, oddball stimuli, and foods); biometric identification accuracy for responses to these item types was compared to that for resting state EEG and "pass-thought" recordings. Results indicated that all

single stimulus-type, single-channel ERP classifiers were more accurate than the pass-thought; the pass-thought classifier was also less accurate than a ERP classifier matched on number of trials included. Single-stimulus type classifiers based on foods and oddball stimuli were the most accurate (86% for the color food, 82% for the black and white food and 80% for the oddball stimuli). This was especially true over the middle occipital electrode, likely due, at least in part, to the visual nature of the task. Further, when multiple channels and/or stimulus types were allowed to vote in identifying a user, identification accuracy reached 100% in several configurations. This exceeds or matches any reported accuracy obtained for any EEG or ERP based classifier– that is, there is no prior report of a 100% accurate ERP biometric, an important benchmark that must be achieved for applied use. In general, the hypothesis that ERPs might provide for especially accurate biometric identification was supported. In particular, we observed that combining responses to multiple types of stimulation provided more accurate identification, on average, than combining an equal amount of data from multiple sensors. This result supports our contention that one reason ERP biometrics are especially accurate is that they provide the ability to tap into functionally distinct brain networks that each provide a distinct identifying information about a person. The limited past work that has explored ERP biometrics ([13], [14]) has not used this approach, of combining types of stimulation, which we suspect may have been why our approach was more accurate.

Prior work has, of course, obtained much higher identification accuracy on the basis of the EEG than the 0% obtained here (e.g., 100% in [5], 98% in [44] and 96% in [9]). One likely reason for this is that we did not perform any feature extraction on the EEG prior to classification. We did this because we wanted to make a fair comparison between EEG and ERPs, where exactly the same data analysis was applied to both. Clearly, it is possible to construct classifiers that produce better performance with respect to the EEG data, for example by considering frequency spectra instead of the raw time domain signal, as was done here. We would not want to conclude that the method we used for analysis of the EEG data here was anywhere near optimal, rather only that ERPs provide such a robustly identifiable signal that little to no feature extraction is needed to obtain very high accuracy identification, whereas much more feature extraction might be needed to reach the same accuracy with EEG.

It seems possible that the oddball stimuli allowed highly accurate classification simply because of the magnitude and robustness of the P300 response they elicited as targets in the participants' behavioral task, and, indeed, the P300 has been the focus of the relatively limited past work conducted with ERP biometrics. One ERP study, for example, made use of the large P300 that is elicited by a self-face embedded in a sequence of non-self faces [14] and achieved 86% verification accuracy (see also [13]); It is less clear why the response to foods was so accurately classifiable. One possibility is that the selection of the foods used here was guided by a norming study which allowed us to select foods that were especially

polarizing in personal preference, however, the same norming was conducted to select the celebrity faces, which were not as accurately classified. Regardless of the explanation for why foods are so accurately classifiable, the discovery that they elicit especially individuating ERP responses highlights the promise of an approach to brain biometrics that considers cognitive and affective elements in the design of challenge protocols.

We are able to achieve 100% identification accuracy only in voting classifiers. As we have discussed in prior work [6], this increase in accuracy when multiple classifiers are combined is a result of the fact that each individual classifier taps at least some percentage of inter-subject variability not shared with other classifiers. This is evident in Figure 5, where it is clear that the brain networks being drawn on by the black and white food classifier are different from those being drawn on by the celebrity classifier or the oddball classifier. The utility of combining multiple types of stimulation is likely part of the explanation for why we were able to achieve 100% identification accuracy here, when even 100% verification accuracy has not been achieved by other ERP biometrics (e.g., [14])— though it would be interesting to compare the CEREBRE protocol to other, related ERP protocols head to head in future work.

Many combinations of stimulus types and channels were able to achieve 100% identification accuracy, which suggests that overall, this protocol is fairly robust. Further, the finding that there are multiple different ways to combine data from this protocol to accurately identify users suggests that this protocol has the added advantage of providing a cancellable biometric. That is, for example, if an authorized user's CEREBRE biometric were stolen or disclosed somehow, the compromised biometric could be cancelled, and a different combination of stimuli/channels could be used for identifying that user after the compromise. Note that other, more prominent, biometric measures, such as fingerprints, retinal scans, and even EKG are non-cancellable. The potential cancellability of the CEREBRE protocol is also one feature that distinguishes it from other ERP biometrics. For example, ERP biometrics that rely on the response to a self-face embedded in a sequence of non-self faces (e.g., [14]) is potentially less cancellable, as it relies on a single, very specific, form of stimulation.

Although the results reported here are extremely promising, there is still clearly more work to be done in investigating the characteristics of this protocol in specific and ERP biometrics in general. First, the resting-state EEG collected here performed extremely poorly, however, we note that the EEG was analyzed in the time domain here to allow more direct comparison with the ERPs, while previous reports of higher accuracy EEG biometric classification have analyzed the EEG in the frequency domain or the combined time/frequency domain (e.g., [9], [44]).

Second, the pass-thought also performed very poorly, despite a seemingly pervasive sense in the general public and also, in some cases, the biometrics community that this should be an effective biometric. However, even when compared with the oddball hamburger classifier, which included a comparable amount of data, the pass-thought performed poorly. Our sense

of why this is the case is that responses to the pass-thought stimulus are likely to be non-uniform, even within a participant, as it is very difficult to focus one's thoughts on a single image or feeling for many seconds in exactly the same way multiple times. And, indeed, our participants self-reported that they had difficulty complying with our directives regarding the pass-thought, as their first thought would normally be about the key itself, and then, after a variable period of time, they would think about their selected memory. Additionally, they reported it was hard to recall the same aspect of the memory each time the key appeared.

Third, all of the stimulation used here was visual; this leaves open the question of whether adding stimulation in other modalities (e.g., auditory, tactile) might also improve the robustness of the ERP classifier— though other sensory modalities in humans do not allow stimulation to be transduced as rapidly as the visual modality, which has the result that ERP time-locking in other modalities can be less crisp than in the visual modality (see, for example, [45]). This may mean that responses to other modalities of stimulation may be more individuating when analyzed in the frequency domain.

Fourth, all data analyzed here were collected in a single session, meaning that the question of the biometric permanence of the CEREBRE protocol is still an open one. Addressing this question will require asking participants to repeat the protocol multiple times with temporal delay between sessions– acquisition of this data is currently ongoing in the lab. Our prior work with ERP biometrics suggests, however, that even at a delay of up to 6 months, ERP biometric identification accuracy does not significantly decrease ([46]). Regardless of these questions for future work, the results reported here suggest that further exploration of ERP biometrics is highly warranted.

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