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A Novel Biometric based on Neural Representations of Synergistic Hand Grasps

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***Abstract*—To meet the growing need of robust and secure identity verification systems, a new biometric based on neural representations of synergistic hand grasps is proposed here. In this preliminary study five subjects were asked to perform six synergistic hand grasps that are shared most often in common activities of daily living. Their scalp electroencephalographic (EEG) signals were analyzed using 20 scalp electrodes. In our previous work, we found that hand kinematics of these synergistic grasps showed potential as a biometric. In the current work, we asked if the neural representations of these synergistic grasps can provide a unique signature to be a biometric. The results show that across 300 entries, the system, in its best configuration, achieved an accuracy of 92.2% and an EER of ~4.7% when tasked with identifying these five individuals. The implications of these preliminary results and applications in the near future are discussed. We believe that this study could lead to the development of a novel biometric as a potential future technology.**

***Keywords*—Biometrics; hand synergies; quadratic discriminant classifier; electroencephalography (EEG); feature extraction**

I. Introduction

In this digital age, an individual's vital signs, exercise, and diet information can be stored on a cloud to be reviewed by an online physician who then sends a prescription wirelessly. This type of streamlined workflow necessitates the need for seamless, secure, and personalized identity authentication. Digitalization has also influenced development of many lower-to-middle income countries to develop cyber infrastructures that records the unique identity of citizens (e.g., India's universal ID program uses biometric identity authentication). The need for robust authentication is also essential in advanced, high profile, defense applications for information security, e.g., DARPA's active authentication program. Such needs are being met by sophisticated methods of authentication provided by biometric systems [1].

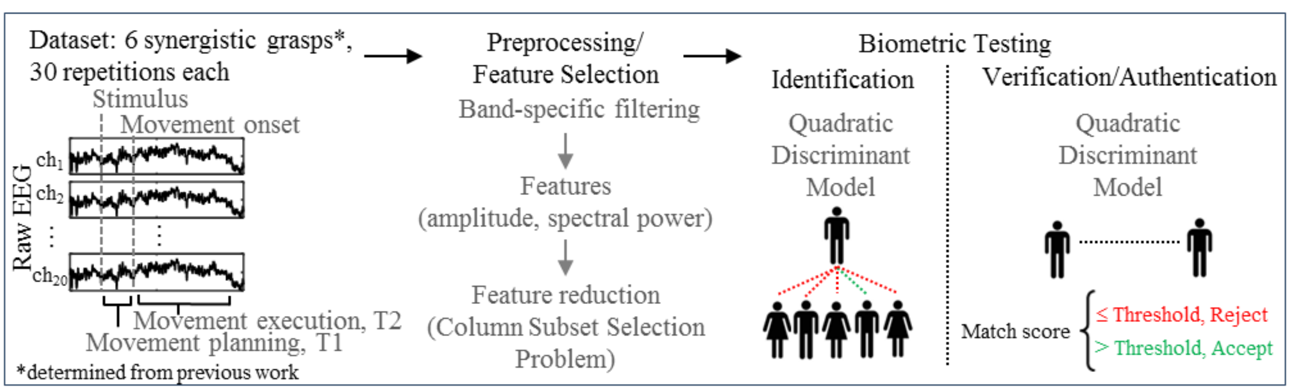

Fig. 1. Based on previous work, unique and representative grasps were determined from a larger grasp set that encompassed activities of daily living. In the current work, we are using the neural representations of these synergistic grasps to determine if unique features can still be extracted at the neural level, as they were as the kinematic level in previous work. EEG is recorded while subjects perform these synergistic grasps. Two functionally differing time segments are tested, movement planning (T1) and movement execution (T2). Features extracted from filtered EEG data are reduced using Column Subset Selection Problem. A quadratic discriminant model is then trained using a subset of the data. For a biometric identification system, a testing entry is treated as a classification problem. For a biometric verification/authentication system, a testing entry must match the model for a particular subject above a given threshold.

Biometric systems can identify individuals based on their physiological characteristics (e.g., finger prints, iris scans, face, recognition, voice recognition, and brain waves) or behavioral characteristics (e.g., typing cadence, gait patterns, and key strokes) or a fusion of these characteristics (multimodal biometrics) [2], [3]. Although they are more efficient than text-based authentication, many of these systems are forgeable due to their stationary nature (snapshots without time history) and yet others are vulnerable due to their lack of uniqueness. Recognizing these limitations and the growing need for biometrics, this proposal presents a new biometric based on hand synergies and their neural representations. The proposed biometric overcomes the current limitations by the following features: 1) unique hand synergies contained in hand movements that are based on an individual's inimitable motor system, motor control and motor learning; 2) dynamic nature of spatiotemporal patterns of hand synergies and their neural representations. Moreover, if a biometric is compromised, existing security systems are in need of replaceable alternatives for cancelable biometrics [4].

Synergy-based movement theory [5] hypothesizes that some commonly used movement patterns are encoded in the central nervous system (CNS). These movement patterns, or synergies, reduce the degrees of freedom that the CNS must control and can be combined to perform more complicated movements. The human hand is one of the most mechanically complex end effectors in the human body and has been studied in the context of hand grasping for many years. We and others have previously explored grasping tasks to determine different forms of movement synergies. In recent work [6], we used twenty-five objects taken from activities of daily living (ADL) to derive kinematic synergies, in the form of joint angular velocity profiles over movement time. We found that these kinematic synergies represented anatomically meaningful joint relationships that execute over time. Testing for sensitivity and specificity of these synergies, we found that they could successfully be used as a biometric. We were able to reduce the larger grasp data set to six objects that still spanned activities of daily living, but also highlighted unique patterns across individuals. Here, we denote these optimized grasps as synergistic grasps. At the kinematic level, these synergistic grasps showed potential as a biometric. In this study, we explored these synergistic grasps at the top level of movement hierarchy, the CNS, to determine if a unique signature can still be found.

The remainder of the paper is outlined as follows. In Section II, a description of the experiment, dataset, and equipment is presented. Then, the steps used to develop the biometric testing scheme are provided. An overview of the system is provided in Fig. 1. In Section III, the performance of this new biometric, evaluated as an identification system and as an authentication/verification system, is presented. An analysis of selected features is also provided. In Section IV, the paper concludes by summarizing the implications of this work and discusses future goals.

II. Methods

A. Data Collection

For this study, five right-handed individuals (3 male, 2 female; mean age 24.8 ± 2.5 years) were recruited under Stevens Institute of Technology Institutional Review Board approval. For EEG data collection, subjects wore a high-density EEG Cap based on 10/20 system positions with an additional 86 intermediate positions (g.GAMMA cap). During the experiment, EEG was recorded with 32 active channels (g.Ladybird). However, for this study, we are considering data from channels most related to motor areas. These channels are: FC_4 (1), C_2 (3), C_4 (2), CP_2 (5), CP_4 (4), RI_1(7) , RI_2 (6), RI_3 (9), RI_4 (8) for right hemisphere, FC_3 (11), C_3 (12), C_1 (13), CP_1 (15), CP_3 (14), LI_1 (16), LI_2 (17), LI_3 (18), LI_4 (19) and Cz (10), CPz (20) along the midline for a total of 20 channels (channel numbers indicated in parentheses). A ground channel was placed at nasion (Nz) and reference channel on the right ear. Fig. 2 (top) shows positioning of these channels. A conductive gel (g.GAMMAgel) was used to bridge the gap between the scalp and each channel. Impedance was kept below 5 kOhms and checked throughout the experiment. Data was continuously captured with two amplifiers (g.USBamp) using BCI2000 [7] at a sampling rate of 256 Hz.

Subjects also wore a right handed CyberGlove (CyberGlove Systems, LLC, San Jose, CA, USA) that records joint angles. For this study we used 10/18 sensors that measured the interphalangeal (IP) and metacarpophalangeal (MCP) joints of the thumb and MCP and proximal interphalangeal (PIP) joints of the four fingers. Each subject performed initial postures to calibrate the glove. Data was captured at 125 Hz using a custom-built LabVIEW (National Instruments Corporation, Austin, TX, USA) program.

Each grasp task consisted of grasping an object placed 40 cm away from the midline of the subject's body (Fig. 2, below). The hand started in an initial resting position (20 cm to the right of the subject's midline). The subject was asked to rapidly grasp the object after hearing an audio 'go' signal and to hold the grasp until an audio 'stop' signal was heard. The LabVIEW program provided these audio cues, collected CyberGlove data, and sent a sync waveform to the amplifiers to align kinematic and EEG data. Subjects were asked to refrain from blinking or swallowing during the grasp, if possible. The six synergistic grasp tasks determined from previous work [6] spanned different grip types (tripod, cylindrical, lateral key, spherical, hook, and precision) found in activities of daily living (ADL). These objects were: screw driver, water bottle, CD, petri dish, handle, and bracelet. Each object was grasped with 30 repetitions, for a total of 180 grasping tasks per subject.

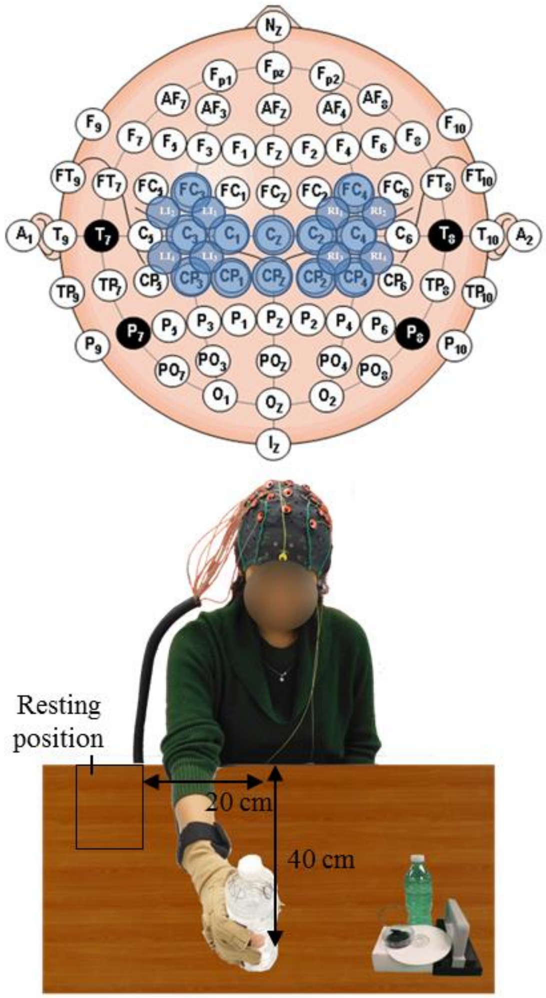

Fig. 2. Top: The twenty selected electrodes and their locations are shown. Left (L) and Right (R) Intermediate (I) electrodes were chosen in addition to traditional electrode positions (frontal—F, central—C, parietal—P), in this high density EEG Cap for improved motorcortical signal acquisition. Bottom: Experimental setup. Subjects grasped six objects representative of activities of daily living. Hand kinematics and neural signals were recorded using CyberGlove and an EEG cap, respectively.

B. Preprocessing

EEG was filtered into 8 different frequency bands: low delta (.01-5 Hz), delta (1-3 Hz), theta (3-7 Hz), alpha 1 (7-9 Hz), alpha 2 (9-12 Hz), beta 1 (13-17 Hz), beta 2 (18-30), and a general EEG band (.01-45 Hz) using a 3rd order Butterworth bandpass filter. As depicted in Fig. 1, we isolated neural data to both movement planning (feedforward neural commands) and movement execution (trajectory correction, sensory feedback) portions. In order to do so, joint data was used to detect grasp onset time (first joint to reach .05% of peak velocity) and completion time (last joint to fall below .05% peak velocity) for each task. Across all subjects the mean onset time (0.5 ± .12 seconds) and grasp completion time (1.45 ± .5 seconds) was calculated. Data taken from 'go' to movement onset is denoted as T1 and from movement onset to grasp completion is denoted as T2. Data was then standardized by subtracting the mean and dividing by the standard deviation (calculated from tasks within the training dataset only) at each time point.

C. Feature Extraction

After splitting data into the 2 groups (T1 and T2), the mean across each time portion was calculated representing the average amplitude of EEG activity for a specific channel and frequency band. We also evaluated the mean power spectral density, using a fast fourier transform (FFT) within this time portion for each frequency band. As a feature type, amplitude and spectral density were evaluated separately. Each feature type resulted in 300 features (8 frequency bands x 20 channels). We first ranked each feature using a column subset selection problem (CSSP) method [8]. After determining the loss of each increasingly ranked feature, the number of features until an asymptote was reached was determined. These n features were chosen to create the training dataset.

Based on preliminary work, we found a quadratic discriminant, rather than a linear discriminant classifier to be a better fit for the distribution of our neural data. In quadratic discriminant analysis, both the means and covariance of each class vary. Additionally, discriminant classifiers can be used for multi-class classification. Here we used data from each of the subjects to represent each class. For initial evaluation of the classifier, 2/3 of the dataset (i.e. 20 repetitions from each of the 6 objects for each subjects for a total of 600 grasps) were used. The remaining 1/3 of the dataset (300 grasps) was used to test the classifier.

D. Biometric Testing

In biometric identification, the system determines the identity of an individual without the individual having to claim it. Thus, we can treat each entry as a classification problem. The classifier chooses the class (here, characterized by covariance matrix and mean) with the least misclassification cost. Accuracy is defined as the percent of correct classifications. In biometric authentication, a claim of identity is given and the system either rejects/accepts the claim. To test this type of system each entry was compared to the user's template (modeled by the quadratic discriminant). The match rate, evaluated as the posterior probability, must be above a specified threshold to be accepted by the system. We evaluated false positive rate and false rejection rate as a function of a threshold to determine equal error rate (EER) of the system.

For initial evaluation of the classifier and to determine strengths of different feature types (amplitude versus spectral density), 3-fold cross validation was used for each time segment (T1 and T2) as well as smaller time windows throughout the grasp time. Finally, selected features from the feature extraction method were examined to determine optimal parameters for this type of biometric. Statistical analysis, when used, was performed using a student t-test with a significance level set at $p < 0.05$.

III. Results

A. Biometric Performance

In order to test the potential of neural sources of synergistic movements as a biometric, a quadratic discriminant classifier was used to classify 5 different subjects. EEG data during grasps were split into two time segments. To evaluate the biometric identification system, the results of classifier performance, averaged across 3-fold cross validation, are presented in Fig. 3. Using amplitude of EEG signals, the classifier achieved 86.6 ± 4.5% accuracy during T1 (movement planning) and 87.2 ± 5.7% during T2 (movement execution). Performance using spectral density was much lower, with an average of 54.4 ± 5.8% and 60.8 ± 6.29% during T1 and T2, respectively.

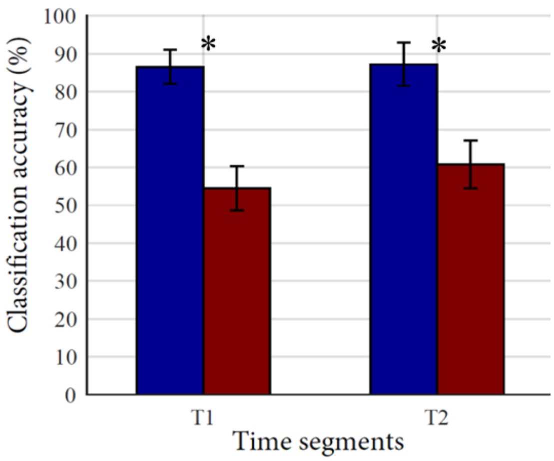

Fig. 3. Classification using amplitude (blue) versus spectral density (red) show significantly better performance ($p < 0.05$) for both T1 (movement planning) and T2 (movement execution), indicated by the *. No significant difference was seen between each of the time segments.

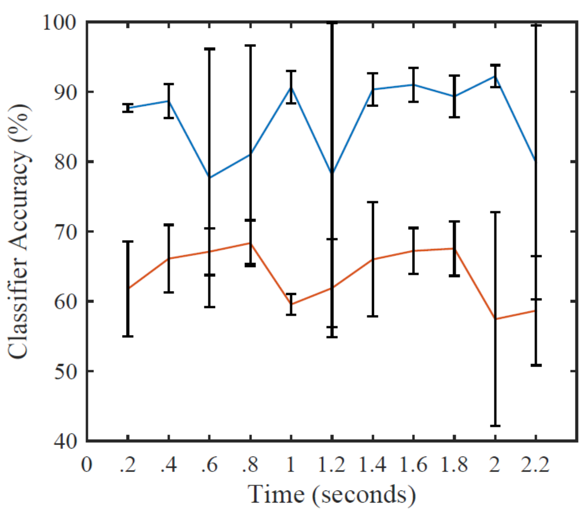

Fig. 4. For both amplitude-based (blue) and spectral power-based (red) classifiers, using a smaller window of data (~1 second) increased performance compared to the longer time windows (T1 and T2). Peak performance was 92.2% at t = 2.0 seconds and 68.3% at t = 0.8 seconds for amplitude and spectral power-based classifiers respectively.

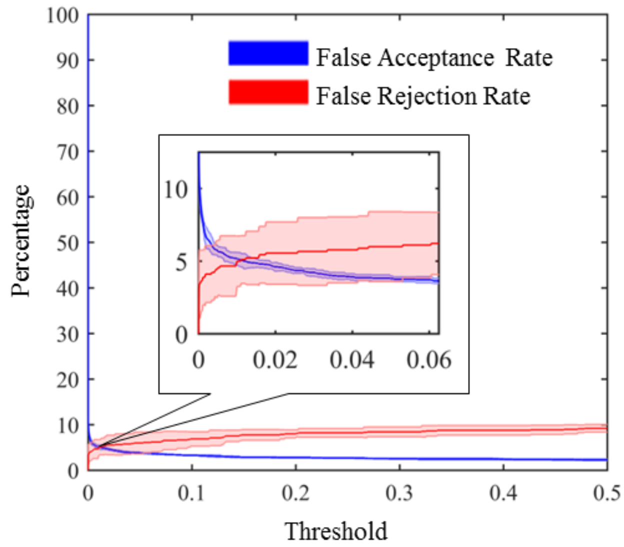

Fig. 5. For a quadratic dimscirmant model based on amplitude features from T1, false acceptance rate (blue) and false rejection rate (red) are plotted ass a function of threshold values (match scores). The inset shows where the two curves meet, to determine EER. Here, EER is ~5.1% at a threshold of .011.

In general, no significant difference could be seen between T1 and T2 for both the amplitude based classifier (p=0.88) and spectral power based classifier (p=0.27). However, neural data during grasping is extremely dynamic, even within T1 and T2. Thus, we further explored how time affects classifier performance using a moving 1-second window of data with ~0.2 second overlap. Results are provided in Fig. 4. For an amplitude-based classifier (blue), results show that accuracy was able to increase to ~92.2 ± 1.57% when using a smaller window towards the end of grasp (time = 2 seconds), thereafter dropping significantly. The spectral power-based classifier (red) also showed increased performance (68.3± 3.8% at time = 0.8 seconds). However, standard deviations across the three folds are high. The classifier, trained on a smaller window of data, may be more sensitive to inter-repetition differences during specific grasp portions (i.e. contact with object).

To evaluate the biometric authentication system, false acceptance rate and false rejection rate are plotted in Fig. 5. The means and standard deviation across 3-fold cross validation is provided by the solid line and shaded region, respectively. The intersection of the two curves represents equal error rate (EER). For T1, EER was ~5.1% using a threshold of .011 (Fig. 5). For T2, EER was ~4.67% using a threshold of .0218. Note that this evaluation was based on amplitude features, rather than spectral power features, based on above results.

B. Feature Analysis

Finally, to optimize such a biometric application, we examined which features were selected during feature reduction. Results, presented in Fig. 6, show features selected from a single training and testing classification iteration for T1 (top row) and T2 (bottom row). Selected bands are shown on the left and channels are shown on the right. For both time periods, the distribution of selected bands and channels is similar. Lower frequency bands and the general EEG band (.01-45 Hz) were most often selected. Although channel 4 was often selected, no spatial trends can be seen from channel selection. During T2, the number of features selected increased, while still maintaining the same distribution.

IV. Discussion and Conclusion

Preliminary results indicate that it is possible to distinguish the identity of an individual based on the neural representations of these six characteristic and synergistic hand grasps. These results, although not substantial, do indicate the potential of neural EEG signals corresponding to synergistic grasps as candidates for biometrics. A biometric system based on these identifiers is currently under development and will be substantiated on a large group of individuals to test sensitivity and specificity. Nevertheless, these preliminary results show promise. Other EEG based biometric systems have been able to achieve up to 100% accuracy in eyes-closed, resting environments [9], [10]. EEG biometrics collected during motor imagery tasks have achieved up to 99% accuracy [11] and those based on stimuli have achieved up to 97% accuracy [12], [13]. An optimal task with high accuracy as well as reproducibility over time remains under investigation. Advantages, disadvantages, applications, challenges and possible solutions for such biometric systems are discussed below.

A. Advantages of Neural(brain) Biometrics

There are several advantages to using neural (brain) activity for biometrics because of its uniqueness, confidentiality, inimitability and invulnerability [14]. Brainwaves have been successfully studied as a biometric for over 15 years [15]. Electrical signals measured by electroencephalogram (EEG) have been used often as a successful biometric due to its simplicity, low cost, noninvasiveness and yet informing macro-scale cortical field potentials. Other noninvasive brain imaging modalities such as magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI), positron emission tomography (PET), and optical imaging and invasive methodologies such as electrocorticography (ECoG) are not considered candidates for use in biometrics due to practical limitations. Functional near-infrared spectroscopy is the only other noninvasive methodology used in biometrics [16].

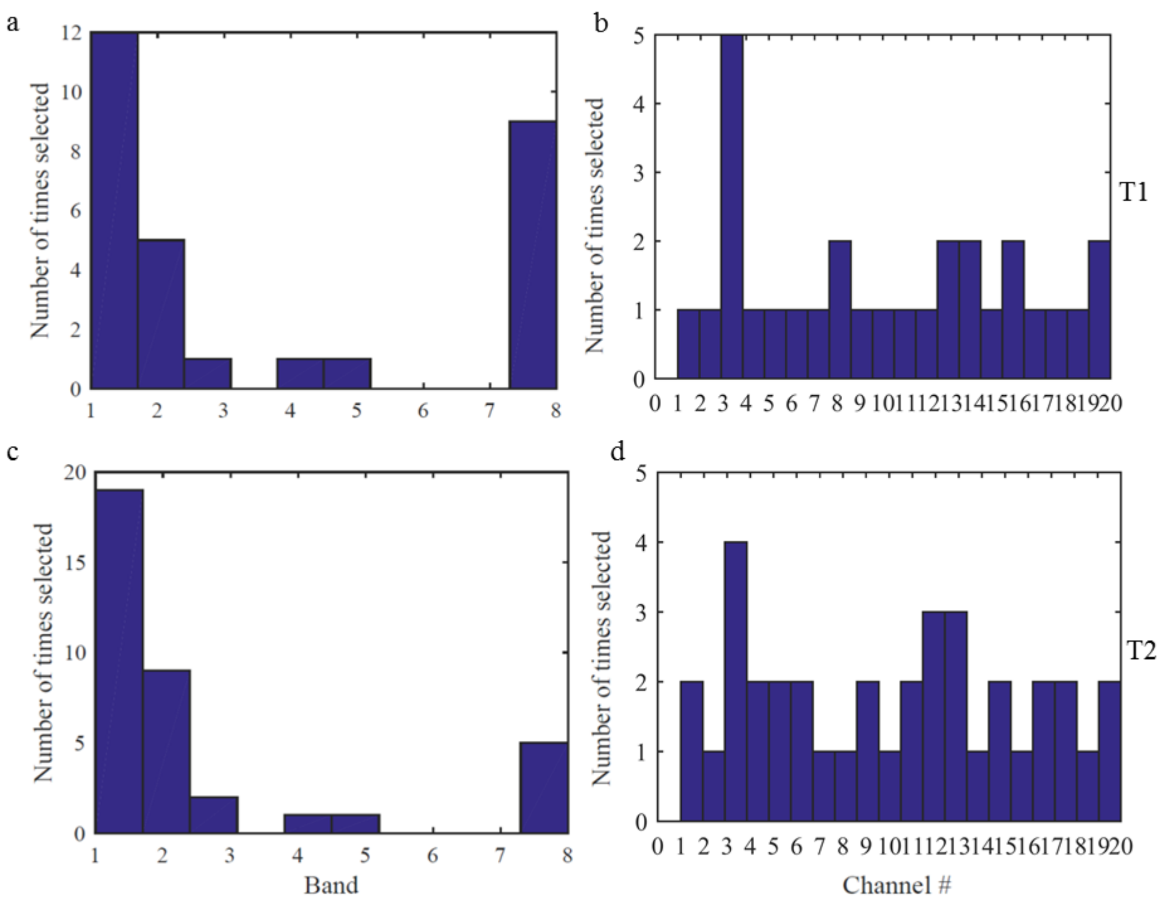

Fig. 6. For time segments T1 (a and b) and T2 (c and d), the distribution of selected features for frequency bands (a and c) and channel numbers (b and d) is the same. Lower frequencies (bands 1-3) and the general EEG band (band 8) were most often selected. Across all 20 channels, only channel 4 shows consistently higher selections. This particular channel lies on the right hemisphere along the central sulcus (RI_2 in Fig. 2, top).

B. Current Challenges of of EEG Based Biometrics

The following studies have used EEG in biometric applications [15], [17]-[19]. Using an autoregressive model, Paranjape et al. [15] examined EEG epochs. Visual evoked potentials (VEP) in 32-48Hz frequency range were used as a biometric by Palaniappan and Mandic [12]. In such studies, subjects are either in a resting state, are performing repetitive self-paced hand movements, generating words, or observing visual stimuli. Current methodologies face challenges such as variability in EEG signals recorded during cognitive tasks at different mental and emotional states, and heritability [14]. By measuring neural representations of physical movements (basic grasping movements) in focal cortical areas we hope to overcome these challenges.

C. Future Challenges and Possible Solutions

Aging affects almost all the biometrics [20]. There are direct and indirect problems associated with aging. Reduction in muscle strength, increase in response time and slow movements are direct problems that can be modeled; indirect problems such as vision deficits, hearing deficits, and other cognitive deficits that affect movement and must be taken into consideration during modeling. A possible solution to these problems is to track changes with age, as done with current biometrics using a data driven approach. This approach can inform the system for needed updates to ensure continued accuracy of the model.

Similar to other behavioral biometrics, the proposed biometric is subject to variability due to disease. Paralysis from stroke and spinal-cord injury (SCI) might completely debilitate one's ability to perform movements. Movement disorders such as Parkinson's disease can introduce tremors into movement. While in some cases, such as SCI, neural representations may remain, in many other cases they may not. Disease is a limitation to this biometric just as upper-limb amputation is to finger prints. Nevertheless, the current study gives us an opportunity to explore this new area of biometrics by studying neural mechanisms of motor control.

REFERENCES

[1] K. Jain, A. Ross, and S. Pankanti, “Biometrics: A tool for information security,” IEEE Trans. Inf. Forensics Secur., vol. 1, no. 2, pp. 125–143, 2006.

[2] K. Jain, K. Nandakumar, and A. Ross, “50 years of biometric research: Accomplishments, challenges, and opportunities,” Pattern Recognit. Lett., vol. 79, pp. 80–105, 2015.

[3] T. H. N. Le, K. Luu, K. Seshadri, and M. Savvides, “A facial aging approach to identification of identical twins,” Proc. 5^{th} IEEE Int. Conf. Biometrics Theory, Appl. Syst., pp. 1–8, 2012.

[4] H. Liu, D. Sun, K. Xiong, and Z. Qiu, “A Hybrid Approach to Protect Palmprint Templates,” vol. 2014, 2014.

[5] R. Vinjamuri, M. Sun, S. Member, C. Chang, H. Lee, and R. J. Sclabassi, “Dimensionality reduction in control and coordination of the human hand.,” IEEE Trans. Biomed. Eng., vol. 57, no. 2, pp. 284–95, 2010.

[6] R. Vinjamuri, V. Patel, P. Thukral, M. K. Burns, I. Florescu, and R. Chandramouli, “Hand Grasping Synergies As Biometrics,” Front. Bioeng. Biotechnol., vol. 5, no. May, 2017.

[7] G. Schalk, D. J. McFarland, T. Hinterberger, N. Birbaumer, and J. R. Wolpaw, “BCI2000: A general-purpose brain-computer interface (BCI) system,” IEEE Trans. Biomed. Eng., vol. 51, no. 6, pp. 1034–1043, 2004.

[8] Ordozgoiti, G. Sandra, and A. Mozo, “A Fast Iterative Algorithm for Improved Unsupervised Feature Selection,” Icdm, pp. 390–399, 2016.

[9] L. Ma, J. W. Minett, T. Blu, and W. S. Wang, “Resting State EEG-Based Biometrics for Individual Identification Using Convolutional Neural Networks,” pp. 2848–2851, 2015.

[10] La Rocca et al., “Human brain distinctiveness based on EEG spectral coherence connectivity,” IEEE Trans. Biomed. Eng., vol. 61, no. 9, pp. 2406–2412, 2014.

[11] J. F. Hu, “New biometric approach based on motor imagery EEG signals,” FBIE 2009 - 2009 Int. Conf. Futur. Biomed. Inf. Eng., pp. 94–97, 2009.

[12] R. Palaniappan and D. P. Mandic, “Biometrics from Brain Electrical Activity: A Machine Learning Approach,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 29, no. 4, pp. 738–742, 2007.

[13] C. Armstrong, M. V. Ruiz-Blondet, N. Khalifian, K. J. Kurtz, Z. Jin, and S. Laszlo, “Brainprint: Assessing the uniqueness, collectability, and permanence of a novel method for ERP biometrics,” Neurocomputing, vol. 166, pp. 59–67, 2015.

[14] Y. N. Singh, S. K. Singh, and A. K. Ray, “Bioelectrical Signals as Emerging Biometrics: Issues and Challenges,” ISRN Signal Process., vol. 2012, pp. 1–13, 2012.

[15] R. B. Paranjape, J. Mahovsky, L. Benedicenti, and Z. Koles, “The electroencephalogram as a biometric,” Can. Conf. Electr. Comput. Eng., vol. 2, pp. 1363–1366, 2001.

[16] Serwadda et al., “FNIRS: A new modality for brain activity-based biometric authentication,” 2015 IEEE 7th Int. Conf. Biometrics Theory, Appl. Syst. BTAS 2015, 2015.

[17] S. Marcel and J. del R. Millan, “Person authentication using brainwaves (EEG) and maximum a posteriori model adaptation,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 29, no. 4, pp. 743–748, 2007.

[18] M. Del Pozo-Banos, J. B. Alonso, J. R. Ticay-Rivas, and C. M. Travieso, “Electroencephalogram subject identification: A review,” Expert Syst. Appl., vol. 41, no. 15, pp. 6537–6554, 2014.

[19] M. V. Ruiz-Blondet, Z. Jin, and S. Laszlo, “CEREBRE: A Novel Method for Very High Accuracy Event-Related Potential Biometric Identification,” IEEE Trans. Inf. Forensics Secur., vol. 11, no. 7, pp. 1618–1629, 2016.

[20] Lanitis, “A survey of the effects of aging on biometric identity verification,” Int. J. Biom., vol. 2, no. 1, p. 34, 2010.