Single-channel EEG-based subject identification using visual stimuli

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***Abstract*—Electroencephalography (EEG) signals have been recently proposed as a biometrics modality due to some inherent advantages over traditional biometric approaches. In this work, we studied the performance of individual EEG channels for the task of subject identification in the context of EEG-based biometrics using a recently proposed benchmark dataset that contains EEG recordings acquired under various visual and non-visual stimuli using a low-cost consumer-grade EEG device. Results showed that specific EEG electrodes provide consistently higher identification accuracy regardless of the feature and stimuli types used, while features based on the Mel Frequency Cepstral Coefficients (MFCC) provided the highest overall identification accuracy. The detection of consistently well-performing electrodes suggests that a combination of fewer electrodes can potentially provide efficient identification performance, allowing the use of simpler and cheaper EEG devices, thus making EEG biometrics more practical.**

***Index Terms*—EEG, biometrics, visual stimulus.**

I. Introduction

The use of electroencephalography (EEG) signals for biometrics has recently attracted interest [1]–[3] due to some advantageous characteristics over traditional biometric modalities, including their resilience to many physical injuries, being extremely hard to reproduce artificially, and the inability to capture them at a distance [4]. Common drawbacks of previously proposed EEG-based biometric approaches are the use of proprietary datasets, the use of medical-grade EEG devices that although offering high quality and high resolution EEG signals, they do not allow the use of EEG-based biometrics in practical scenarios, and the evaluation of proposed methods on EEG signals acquired during a single session, thus not examining the effect of template ageing, i.e. "*the increase in error rates caused by time-related changes in the biometric pattern, its presentation and the sensor*" [5]. Furthermore, the absence of public benchmark datasets for EEG-based biometrics has led many studies to utilise EEG datasets that were designed for other tasks, e.g. emotion recognition [6]–[8], thus not allowing the study of specific signal acquisition protocols that would be more suited for biometrics.

To address these drawbacks, a public benchmark dataset called "Biometric EEG Dataset" (BED) [9] was recently proposed for EEG-based biometrics. The BED dataset contains EEG recordings from 21 individuals that were acquired during three separate sessions, each one week apart. Furthermore, EEG signals were captured while the subjects were exposed to various visual and non-visual stimuli in order to allow the study of various EEG acquisition protocols. Furthermore, EEG signals in the BED dataset were acquired using a relatively inexpensive consumer-grade wireless EEG device in order to facilitate the creation and evaluation of algorithms and protocols that would be suitable for practical use. Subject identification performance on the BED dataset was originally evaluated by combining the features extracted from the 14 available EEG channels (electrodes) and using them to train machine learning models. However, if similar identification performance can be achieved using less electrodes, then simpler and cheaper EEG devices could potentially be used, thus significantly enhancing the practicability of EEG biometrics.

To this end, in this work we studied the performance of individual EEG channels for the task of subject identification. We modified the baseline evaluation experiments of the BED dataset by first extracting the proposed features from each individual EEG channel and then training separate machine learning models for each EEG channel for the task of subject identification. Results using three different types of features and the EEG recordings associated with nine different visual stimuli showed that some EEG electrodes provided consistently high identification accuracy regardless of the feature and stimuli types. Furthermore, similar to the available baseline results, features based on the Mel Frequency Cepstral Coefficients (MFCC) provided the highest overall identification accuracy, as well as the best identification accuracy for each EEG electrode apart from F4 and F7. Furthermore, the highest single-channel identification accuracy achieved was lower than the previously reported baseline multi-channel accuracy, indicating that different electrodes contain complementary biometric information.

II. Methodology

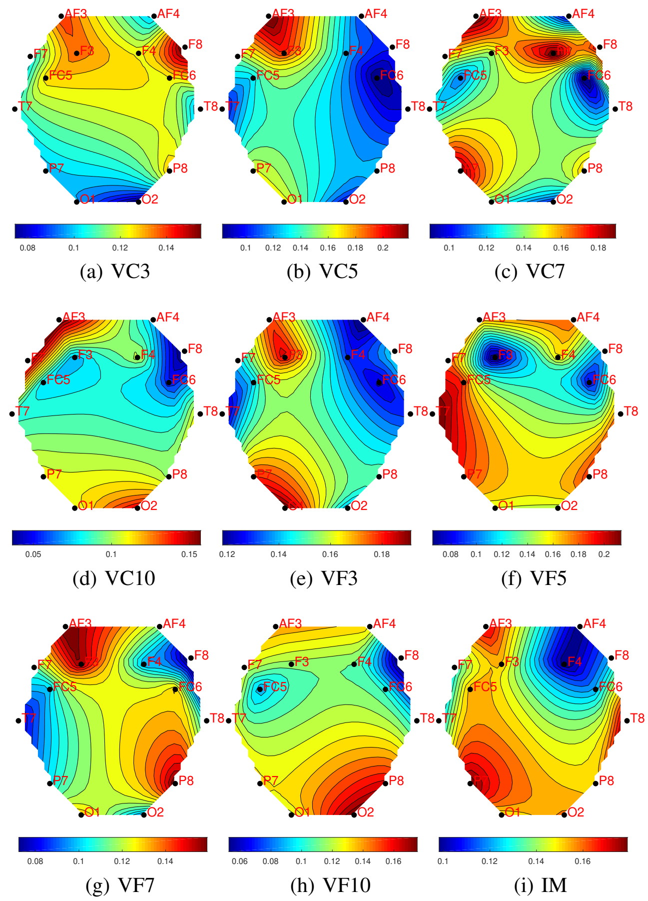
The BED dataset [9] was selected for studying the performance of individual EEG channels for the task of biometric subject identification. BED is a recently released dataset designed for EEG-based biometrics using low-cost consumer-grade EEG devices. BED contains EEG recordings acquired from 21 healthy individuals while presented with 12 different types of stimuli. Stimuli consisted of images aiming at eliciting specific emotions (IM), mathematical computations, Visual

Evoked Potentials (VEP) at 3, 5, 7, and 10 Hz with the standard checker-board pattern with pattern reversal (VCx, $x = 3, 5, 7, 10$), and flashing VEP with flashing black colour at 3, 5, 7, and 10 Hz (VFx, $x = 3, 5, 7, 10$). Furthermore, EEG signals where acquired during three separate sessions spaced one week apart, in order to allow the study of template ageing. The Emotiv EPOC+ [10] wireless EEG headset was used in order to record a 14-channel EEG signal via contact sensors placed in locations that closely align with the AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 locations of the international 10-20 system.

Baseline results for subject identification were provided for BED in [9], where the EEG signals were segmented into segments of 5 s length with 50% overlapping, pre-processed to remove noise and artefacts, and MFCC features, Autoregression Reflection Coefficients (ARRC) features, and Spectral features (spectral centroid, spectral bandwidth, spectral crest factor, and spectral flatness) were computed for each segment. The problem of subject identification was then modelled as a multi-class classification problem where each class referred to an individual subject (21 classes). To account for the issue of template ageing, the multi-class models were trained with the data from the first two sessions and tested with the data from the third session. A multi-class ensemble classifier was trained and tuned for each type of stimulus and features. Baseline results showed that for all types of features, the highest accuracies were achieved for the "*Resting with eyes closed*" stimulus, reaching 47.79% for the MFCC features. When only visual stimuli are considered, the highest classification accuracies were achieved for the "*Images with emotional content*" stimulus, reaching 40.25% for the MFCC features [9].

In this work, contrary to [9], to examine the performance of individual EEG channels, each model was trained and tested using features extracted from each individual channel, resulting in the creation of 14 multi-class models for each of the three features and each of the nine visual stimuli. Similar to [9], the EEG signals were pre-processed using the EEGLAB toolbox [11] to apply the PREP pipeline [12], consisting of line-noise removal via filtering, referencing the signal relative to the estimate of the "true" average reference, and finally detecting and interpolating bad channels relative to the reference. Then, similar to the baseline BED experiment [9], the MFCC features were computed by first applying the Fourier Transform, followed by a filterbank in the Mel scale, and the Discrete Cosine Transform. A filterbank with 18 filters was used and the first 12 coefficients after dropping the D_C component were selected as the MFCC features. Then, 12 ARRC features were computed using a 12$^{\text{th}}$ order autoregressive model, created by solving the Yule-Walker equations. Finally, the spectral centroid, spectral bandwidth, spectral crest factor, and spectral flatness features [13] were computed from the theta (4-8 Hz), alpha (8-12 Hz), beta (12-30 Hz), and gamma (30+ Hz) bands of the EEG signal, leading to a total of 16 spectral features.

The computed features were then used in order to train and test multi-class ensemble classification models for all the combinations of electrodes, features, and stimuli, resulting in a total of 14 electrodes $\times$ 3 features $\times$ 9 stimuli $=$ 378 trained models. Similar to [9], the subject identification problem was modelled as a 21-class classification problem were each class was associated with one individual from the dataset. Matlab (R2016b) was used for training and tuning the classifiers. To this end, the built-in Matlab's hyperparameter optimisation approach was used in order to select the optimal ensemble aggregation method, as well as the optimal learning parameters, by exhaustively testing configurations and selecting the one that results to the minimum estimated cross-validation loss. The examined ensemble aggregation approaches used decision trees as the week learners and included bootstrap aggregation, random subspace aggregation, adaptive boosting, linear programming boosting, random undersampling boosting, and totally corrective boosting. It must be noted that the results reported in the next section refer to the optimal configuration for each trio of electrode, feature, and stimulus.



(a) VC3 (b) VC5 (c) VC7
(d) VC10 (e) VF3 (f) VF5
(g) VF7 (h) VF10 (i) IM

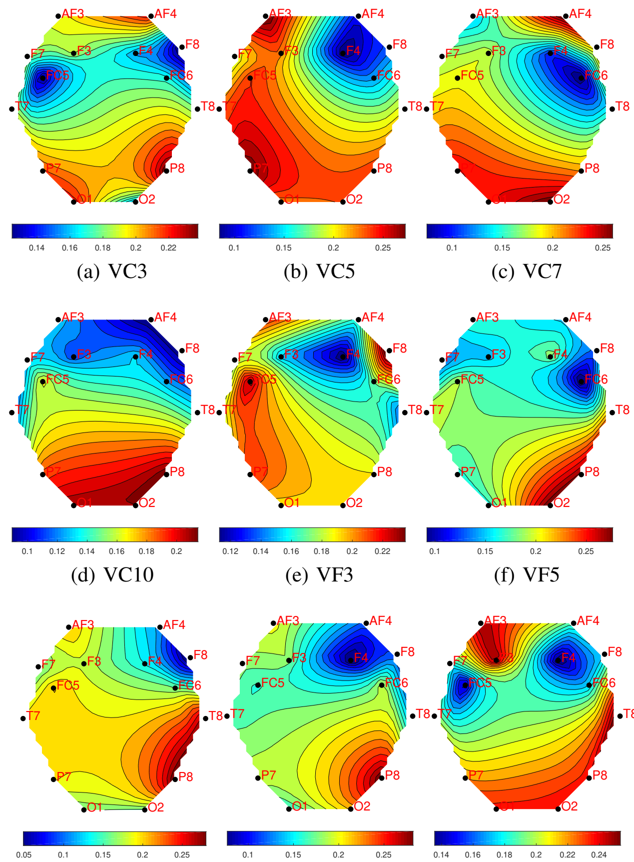
Fig. 1: Identification accuracy using the ARRC features.

III. Results

The results of the supervised classification experiments for subject identification are presented for each EEG electrode (channel) and stimulus in Fig. 1, 2, and 3 for the ARRC, MFCC, and Spectral features respectively. In these figures, accuracies have been plotted as a heat map in relation to the location of each electrode on the human scalp. By examining these heat maps, it is evident that some electrodes, such as AF3, P7, P8, O1, and O2, led to higher identification accuracies in most cases compared to other electrodes. This observation is consistent with the findings of previous studies [14], [15] that utilised the same EEG device as the BED dataset for the task of EEG biometrics and suggested that biometric signatures should be extracted from the P7, P8, O1, and O2 electrodes when users are exposed to visual stimuli. To further investigate this observation, we selected the four electrodes that provided the highest accuracy for each stimulus and each feature type and we measured how often each electrode was among the top four performing for each feature and stimulus type (3 features $\times$ 9 stimuli $=$ 27 cases per electrode). Results, were consistent with the above observation, with electrode AF3 being in the top four for 67% of the cases, P7 for 63% of the cases, P8 56%, O1 44%, and O2 41%, as shown in TABLE I.

The highest subject identification accuracy achieved for each electrode and each feature type is reported in TABLE II. The highest accuracy (29.69%) was achieved using the P8 electrode and the MFCC features for the flashing VEP at 7 and 10 Hz (VF7 and VF10). For the Spectral features, the highest accuracy of 25.26% was achieved using again the P8 electrode for the image stimulus, whereas for the ARRC features, the highest accuracy of 23.14% was achieved using the AF3 electrode and the checker-board VEP at 5 Hz (VC5). Another interesting observation is that different types of stimuli performed better for each type of features used. From TABLE II, it is evident that the flashing VEP at 5 Hz provided the best accuracy for most electrodes when the ARRC features were used, the checker-board VEP at 5 Hz for the MFCC features, and finally the images with affective content (IM) performed best for the Spectral features.

Comparing the acquired results for the single-electrode approach with the results for the baseline approach [9] that utilised all electrodes, it is evident that the single-electrode approach underperformed considerably (29.69% vs 40.25% accuracy). This finding indicates that the biometric information encoded in the EEG signal of various electrodes is complementary and the combination of multiple electrodes can lead to higher identification accuracy, as also suggested in [14] and [15], where the authors combined the signals from the P7, P8, O1, and O2 electrodes. Nevertheless, similar to the baseline approach in [9], the MFCC-based features provided the highest overall accuracy, while consistently achieving the highest accuracy among the three feature types for each EEG electrode apart from electrodes F4 and F7 where they performed marginally worse, as shown in TABLE II. In addition, the detection of consistently well performing electrodes (AF3, P7, P8, O1, O2) across various feature and stimuli types shows that less electrodes can potentially be used for the task of EEG-based biometric identification, allowing simpler and cheaper EEG sensors to be used, thus increasing the potential user-friendliness and viability of EEG-based biometrics.



(a) VC3 (b) VC5 (c) VC7

(d) VC10 (e) VF3 (f) VF5

(g) VF7 (h) VF10 (i) IM

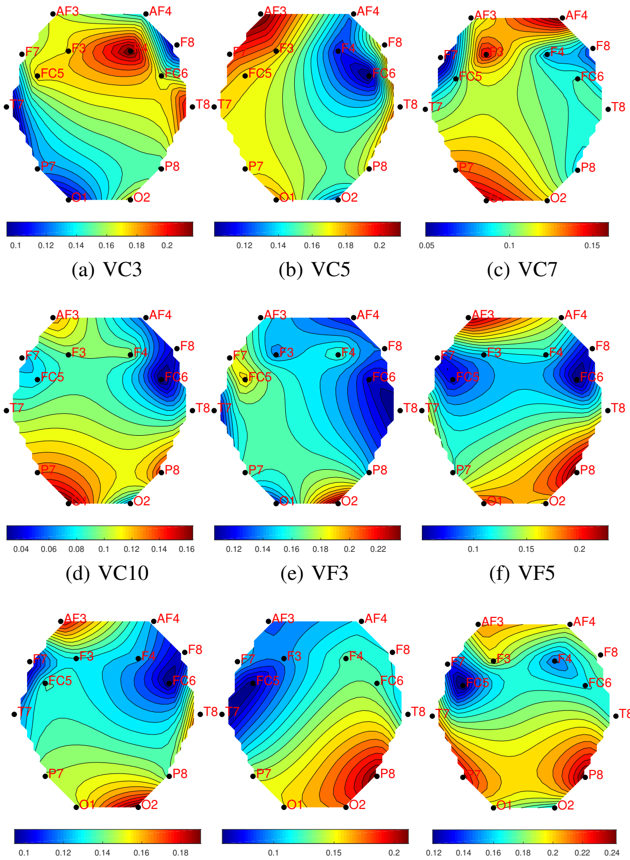
Fig. 2: Identification accuracy using the MFCC features.

TABLE I: Frequency of each electrode being among the four best performing electrodes for each feature and visual stimulus.

Electrode	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
Location	**AF3**	**F7**	**F3**	**FC5**	**T7**	**P7**	**O1**	**O2**	**P8**	**T8**	**FC6**	**F4**	**F8**	**AF4**
ARRC	8	1	4	1	1	6	3	3	4	2	1	1	2	1
MFCC	5	0	1	3	1	5	3	4	7	3	1	0	1	2
SPECG	5	2	2	2	2	6	6	4	4	3	0	1	0	1
SUM	18	3	7	6	4	17	12	11	15	8	2	2	3	4
(%)	67	11	26	22	15	63	44	41	56	30	7	7	11	15

IV. Conclusion

In this work, we examined the performance of individual EEG channels for the task of EEG-based subject identification using a low-cost consumer-grade EEG device. The results of the supervised classification experiments showed that the AF3, P7, P8, O1, and O2 electrodes provided the best identification accuracy for the majority of feature and stimuli types, while the MFCC-based features provided the highest overall accuracy, as well as the highest accuracy among the features examined for each electrode apart for F4 and F7. However, the lower identification accuracy of the single-electrode approach, compared to using all the electrodes, indicates that there is complementary biometric information across different electrodes. The detection of consistently well performing



(a) VC3 (b) VC5 (c) VC7

(d) VC10 (e) VF3 (f) VF5

(g) VF7 (h) VF10 (i) IM

Fig. 3: Identification accuracy using the Spectral features.

TABLE II: Highest identification accuracy achieved for each electrode and feature using visual stimuli.

		ARRC		MFCC		Spectral	
Channel	**Location**	**Accuracy (%)**	**Stimulus**	**Accuracy (%)**	**Stimulus**	**Accuracy (%)**	**Stimulus**
1	AF3	**23.14**	VC5	28.82	VC5	22.81	VF5
2	F7	18.42	VF5	19.21	VC5	19.65	VC5
3	F3	20.09	VC5	25.67	IM	19.71	IM
4	FC5	19.30	VF5	24.45	VC5	19.67	VF3
5	T7	22.81	VF5	23.14	VC5	21.56	IM
6	P7	19.47	VC7	28.38	VC5	23.61	IM
7	O1	19.67	VF3	23.82	IM	20.18	VF5
8	O2	18.34	VF10	28.95	VF5	24.59	VF3
9	P8	19.30	VF5	**29.69**	VF7/10	**25.26**	IM
10	T8	18.42	VF5	27.95	VF7	21.65	VC3
11	FC6	13.54	VF7	20.09	VF10	16.63	IM
12	F4	20.35	VC7	19.30	VF5	22.94	VC3
13	F8	18.58	VC7	25.41	VF3	18.48	IM
14	AF4	18.42	VF5	27.43	VC7	19.71	IM

electrodes suggests that a combination of fewer electrodes can potentially provide efficient identification performance, thus allowing the use of simpler and cheaper EEG devices with less electrodes that would make EEG-based biometrics significantly more practical and user-friendly.

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