Modeling of Olfactory Brainwaves for Odour Independent Biometric Identification

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***Abstract*—Brainwave captured through electroencephalogram (EEG) is a promising potential biometric for subject identification. EEG can be acquired, when the subject is exposed to external stimuli such as visual triggers or when the subject is resting. During biometric identification, expecting a person to be in a resting state, is not realistic; also external stimuli introduce artifacts in acquired EEG signals resulting in poor performance of EEG-based biometric systems. Odours evoke natural emotions in humans by associating strong memories with a particular smell. As a result, odours can be a potential stimulus for generating strong brainwaves; and unlike other triggers, odours can produce EEG without prominent artifacts. In this paper, an olfactory brainwave-based biometric system is proposed, where we model the subject-specific characteristics from the EEG signals captured using different odours as the trigger. We extract, from EEG signals, a set of hand-crafted and diversified spectro-temporal features to train a biometric model. Experiments conducted on a publicly available dataset, show that it is possible to build an odour-independent biometric system with high-performance accuracy. Additionally, using odour-chemistry literature, we show that a small set of carefully chosen odours are sufficient to build a high-performance biometric system.**

***Index Terms*—EEG Biometry, Subject Identification, EEG, Olfactory brainwaves, Odour Stimulus.**

I. Introduction

Authentication and identification can be classified into three groups: User Knows (UK), User Has (UH) and User Is (UI) [1]–[3]. In UK and UH categories, users have passwords and personal identification numbers (PIN), which can be forgotten, lost or stolen; thus resulting in unsuccessful authentications, information leakage and security threat. UI category is not susceptible to such problems, because it relies on the innate physiological signals from an individual and therefore, cannot be lost or stolen. It is a better option for a reliable biometric system. Since brainwaves capture a person's innate physiological behavior and fall in the UI category, a biometric system based on brainwaves is a promising candidate for robust and secure personal identification and authentication [4]–[6]. In principle, the biometric system extracts patterns from the signals captured from a person and stores them, and then compares them with the same set of extracted features from the signal acquired while authenticating the person [7]. Unlike fingerprints, iris and face recognition-based biometric systems which can be compromised using gummy fingerprints, contact lenses, and 3D printed faces respectively, EEG-based systems are not easily compromised because the brainwaves are unique for every individual and originate inside the brain [8], [9]. Brain signals are characterized by original patterns for a specific individual; thus, are capable of providing security and privacy to a person in a biometric identification setting. Additionally, brainwave-based biometry can be one of the best alternatives for people with severe damage and deformation of their physical structure because of accidents or injuries.

Electroencephalogram (EEG) is the most widely used mechanism to capture brainwaves, primarily because it facilitates fine temporal resolution, low setup cost and most importantly, is non-invasive. It is known that even slight eye movements, changes of gaze and, jaw muscle movements can introduce artifacts (noise) in the captured EEG signal even from a subject who is resting, with or without their eyes open [7], [10]–[14]. Therefore, it is difficult to extract person-specific features from such noisy EEG signals for biometric identification without any external stimuli. To enable EEG signals to capture person-specific characteristics, instead of resting, the subject can be exposed to external stimuli such as listening to an audio, or watching visuals, or following audio-visual instructions to imagine [8], [15]–[17]. These external stimuli activate neurons in different parts of the brain, resulting in amplified event-related potential (ERP) which can mask the noisy artifacts. Interestingly, both sides of the brain hemisphere have certain frequency band ERPs which strengthen the EEG power spectrum when an external stimulus is present and weaken when an external stimulus is absent [18]. Analysis of EEG signals, acquired from subjects asked to imagine speech, for biometric identification, has been reported in [19]–[21]. The primary problem with audio-visual stimuli is that they introduce more artifacts into EEG, and most importantly it is unclear if the artifacts are a result of direct contamination of signals due to stimuli or natural brain response to the stimuli. The mix of brain signals and artifacts makes it impossible to segregate and use only the brainwaves resulting from the stimulus for extracting person-specific features to be used in a biometric system. Therefore, unlike the audio-visual stimulus, it is better to consider a stimulus that has little or no effect in direct contamination of the EEG recordings.

Odour has been shown to induce significant changes to human psychophysiology such as positive effects on mood, stress, anxiety and depression [22]–[25]. Odour can be a potential stimulus for generating strong brainwaves that capture person-specific characteristics for biometric identification

because (a) odours evoke emotions resulting in brain activity because of the strong memory-smell association in people, and (b) unlike audio and visual triggers, odours do not result in additional artifacts alongside the signals due to normal brain activity. There are studies on olfactory EEG signals in the literature, for example, [26]–[28]. Most of them focus on odour identification or odour categorization. To the best of our knowledge, use of EEG signals for biometric identification with odour as a trigger has never been attempted. Our motivation to explore odour for biometric applications was strengthened when we observed that (a) the brain activity varied significantly for different people, and (b) an individual showed similar brain activity across different odours. Figure 1 depicts the t-SNE visualization of 5005 EEG signals[1] acquired from 11 subjects, triggered by 13 different odours. Each subject, represented by a different color in Fig. 1, appears together in a cluster and more importantly, there is no overlap across different subjects. Thus, subject-wise EEG samples form non-overlapping and unique clusters as shown in Fig. 1 where the EEG samples corresponding to `sub10` appear in two clusters without over-lapping with any other subject.

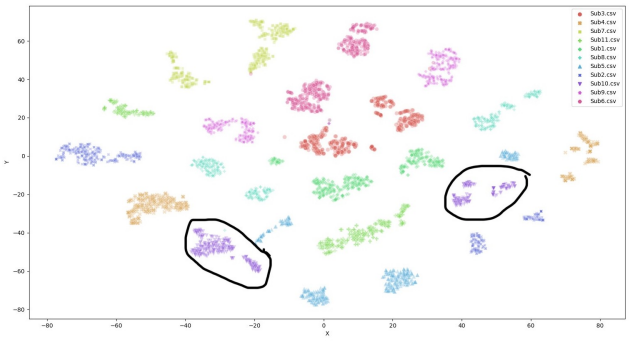

Fig. 1. t-SNE plot: EEG samples from 11 subjects exposed to 13 odours, each with 35 trials; samples across subjects create non-overlapping clusters (for example, Sub10 at two places marked shows distinct cluster)

In this paper, we propose to use the EEG signal acquired from a person, subjected to odour stimuli, for biometric identification. Person-specific characteristics are modeled from the EEG signals captured with different odour as triggers. As is common, we extract a set of hand-crafted and diversified biomarkers in the spectro-temporal domain from the raw EEG signal to train the biometric model. In particular, we aim to build an odour-independent person identification system that is suitable for realistic applications. We show through a series of experiments, with a publicly available dataset, that it is possible to build a high-accuracy, odour-independent biometric system. We further demonstrate that using knowledge of odour chemistry, a small set of carefully chosen odours are sufficient to build a high-performance biometric system. This is one of the main contributions of the paper. The rest of the paper is organized as follows: in Section II, we discuss the proposed approach for a smell-independent biometric system. The experimental setup is described in Section III. Results and analysis are provided in Section IV. We conclude in Section V.

[1]35 EEG signals per person per odour

II. Odour-based Biometric System

The objective is to build a biometric system, using the EEG signal acquired from a person in response to odour stimuli. We use the features extracted from the raw EEG signal to train a multi-class classifier. The class labels correspond to the total number of subjects that need to be identified.

We extract both temporal and spectral features to derive useful information from the raw EEG signal acquired in response to odour stimuli. Specifically, we extracted (see Table I) conventional temporal features, namely, Hjorth mobility and complexity parameters; detrended fluctuation analysis (DFA); fractal dimension with Higuchi (HFD) and Petrosian algorithms (PFD); Hurst exponent (Hurst) computed on the entire signal as mentioned in [29].

Feature Set	Features	Bands	Dim/Channel
`PyEEG`	Power Spectral Intensity (PSI) and Relative Intensity Ratio (RIR), Hjorth mobility and complexity, Petrosian Fractal Dimension (PFD), Higuchi Fractal Dimension (HFD), Spectral Entropy (Shannon's entropy of RIRs), Detrended Fluctuation Analysis (DFA), Hurst Exponent (Hurst)	θ: 4-8Hz α_{low}: 8-10Hz α_{high}: 10-13Hz β: 13-25Hz γ: 25-40Hz	9
`BioSPPy`	Average signal power, with overlapping windows, in EEG frequency		5
`PyWavelets`	Energy, Entropy, RMS, REE, LREE, ALREE	θ: 4 - 8Hz α: 8-13Hz β: 13-25Hz γ: 25-40Hz	24

TABLE I: Details of EEG features used in our experiments.

The EEG signal is transformed into a frequency domain using fast Fourier transformation (FFT), followed by extracting three spectral features, namely, power spectral density (PSD), relative intensity ratio (RIR); and spectral entropy. In addition, we extract discrete Wavelet transformation (DWT) based spectro-temporal features using `db4` wavelet [30], [31]. These features are: energy; entropy; root mean square (RMS); recursing energy efficiency (REE); logarithmic REE (LREE), and absolute logarithmic REE (ALREE). Note that these spectral features are extracted separately for the 5 standard EEG bands, namely, θ (4 - 8 Hz), α_{low} (8 - 10 Hz), α_{high} (10 - 13 Hz), β (13 - 25 Hz) and γ (25 - 40 Hz). These EEG features are in literature (see [26]) so we do not elaborate on them here.

	`PyEEG`	`BioSPPy`	`PyWavelets`	Early	Late
SVM	96.74 ± 4.62	95.22 ± 6.00	93.55 ± 10.46	96.34 ± 6.92	$\mathbf{99.72} \pm 3.21$
RF	96.62 ± 4.28	97.36 ± 2.63	97.94 ± 1.96	98.62 ± 1.59	$\mathbf{99.80} \pm 1.12$
KNN	95.74 ± 6.67	95.80 ± 4.64	96.16 ± 5.21	96.80 ± 4.98	$\mathbf{99.86} \pm 3.14$
ANN	95.22 ± 5.30	95.78 ± 5.22	93.41 ± 9.58	94.53 ± 10.40	$\mathbf{99.61} \pm 4.21$

TABLE II: Average person identification accuracy and variance over 13 *leave* 1-*odour out* experiments.

The odour-based biometric system is a multi-class classifier with features extracted from the EEG signal as the input. We ensure that the odours (used as stimuli for acquiring EEG data) used for testing the biometric system are not

	PyEEG	BioSPPy	PyWavelets	Early	Late	# odours
SVM	49.70	50.04	50.93	53.16	50.37	1
RF	55.30	**57.84**	49.42	52.12	55.71	
KNN	45.69	46.75	51.80	55.00	47.86	
ANN	50.06	52.19	55.37	56.08	51.69	
SVM	62.99	61.79	61.49	62.92	62.92	5
RF	67.08	**72.11**	65.10	65.16	64.67	
KNN	62.99	62.66	64.25	64.35	63.21	
ANN	63.25	63.54	62.50	61.95	64.06	
SVM	90.48	90.04	83.03	89.18	88.74	10
RF	87.62	97.49	91.17	99.74	95.93	
KNN	84.94	89.44	85.54	87.53	88.66	
ANN	85.71	92.29	99.22	**100.00**	97.4	

TABLE III: Odour biometric with random odour selection.

part of the training data, thus making the biometric system independent of odour. While one can hypothesize that an increase in the number of odours used during training will result in a better-performing biometric system, we show that it is indeed possible to achieve a high-performance biometric system, using as few as 4 or 5 odours derived by exploiting an understanding of odour chemistry.

III. Experimental Setup

We use the publicly available odour-EEG dataset (ODOUR-DB) [32] for training our odour-independent biometric system and validating its performance. The ODOUR-DB consists of a 32 channel EEG signal recorded using the Cerebus system from 11 healthy individuals (8 males and 3 females), right-handed, aged 24.9 ± 3.0 years in response to 13 odour stimuli (rose, caramel, rotten smell, canned peaches, excrement, mint, tea, coffee, rosemary, jasmine, lemon, vanilla, and lavender). Of the 32 channels, 2 are reference channels, making it 30 usable channels for analysis. The electrodes for collecting EEG are arranged according to the international 10-20 system, and sampled at 1 kHz. Each sample collected was for a duration of 10 seconds, called a trial. In total, ODOUR-DB has 11 (participants) $\times$ 13 (odours) $\times$ 35 (trials) resulting in a total of 5005 EEG samples.

We used (a) `PyEEG` [29] toolbox, specifically designed for EEG signal analysis, to extract the temporal features in addition to spectral entropy and relative intensity ratio features, (b) `BioSPPy` toolbox [33] to extract spectral features from each EEG band and (c) `PyWavelets` toolbox [34] to extract DWT based features. In all our experiments, PSD and DWT features are extracted for a window length of 25 msec with an overlap of 12 msec, further we decomposed the EEG signal till the 7^{th} level (DWT) for the bands θ, α, β, γ. The complete list of the features used in our experiments is captured in Table I. In all, we had three sets of feature consisting of 9 (`PyEEG`), 5 (`BioSPPy`) and 24 (`PyWavelets`) features extracted per channel. Note that each EEG signal consists of 30 channels.

To build a biometric identification system, we implemented 4 different classifiers, namely, Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbour (KNN) and Artificial Neural Network (ANN) from the `scikit-learn` python toolbox. SVM classifier is based on `libsvm`, with regularization set to 1 with a linear kernel. In the RF classifier the number of trees was set to 100, and in KNN the number of nearest neighbors was set to 5. In ANN, we have used 100 hidden layer neurons, with `relu` as the activation function and `Adam` stochastic gradient-based optimizer for weight optimization of batchsize 2. The learning rate was constant and set as $r = 0.0001$. We used classification accuracy as a metric to evaluate the performance of the biometric system.

IV. Results and Analysis

In the initial set of experiments, we took EEG signals corresponding to 12 out of the 13 odours (*leave* 1*-odour out*) available in the dataset to model the subject's brainwave characteristics and train a biometric identification system. Experimental results with three different feature sets and 4 different classifiers are shown in Table II. Also included in Table II are results associated with (a) early fusion (the features from `PyEEG`, `BioSPPy` and `PyWavelets` are concatenated into one large feature set which is then used for classification) and (b) late fusion (aggregates predictions of three individual classifiers trained using the three feature sets separately). The *leave* 1*-odour out* experiment shows that all 12 combinations of feature sets and classifiers result in comparable performance. However, late fusion-based biometric system performance shows average accuracies of around 99%.

In the next set of experiments, we picked a subset of odours, at random, to model the subject and tested on the remaining odours. Table III shows the result for 1, 5, and 10 odours used for subject modeling and the remaining 12, 8 and 3 odours are respectively used for testing. As can be seen, the performance of the biometric system increases with an increase in the number of odours used for modeling the subject. Observe that all the systems using 10 odours to model the subject perform much better (accuracies in the range 83.03% - 100%) than the best-performing 5-odour (72.11%) and 1-odour (57.84%) systems. This is in line with our hypothesis that a biometric system built with a larger number of odours should perform much better than a system trained with a lesser number of odours.

In the next set of experiments, we wanted to explore if there was a way of *selecting* a *small* set of odours instead of selecting as many odours as possible without any performance degradation of the biometric system. In other words, if there is a small set of odours that more or less capture the global odour profile of a person.

Very early work [36] showed that any odour can be represented as a 4-component system, namely, a weighted mix of `fragrance`, `acidity`, `burntness`, and `caprylicness`. Every odour has a bit of each component, enabling any odour to be represented by a four-digit number, where the number indicates the intensity of the component [37]. For example, freshly roasted coffee can be represented as $(7, 6, 8, 3)$ while hay can be represented as $(5, 1, 1, 4)$. To enable a plausible interpretation of the 4 components, odour profiles of 144 aroma chemicals were extracted and compared to numeric odour profiles through statistical regression [35]. This resulted in the visualization of the odour cube. Using

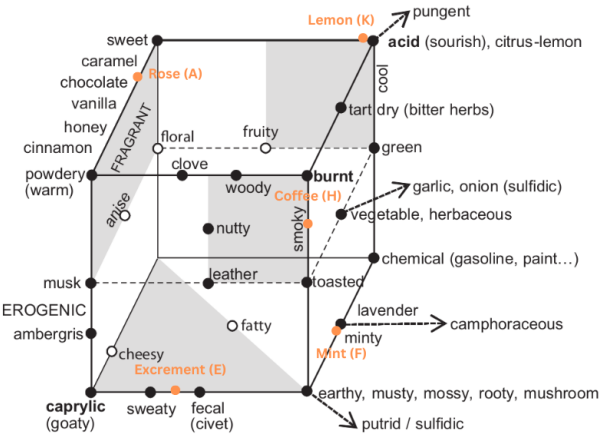

Fig. 2. The selected odours marked on the Odour Cube [35].

an odour cube as a reference, we identified a set of 5-odours, among the 13 odours available in ODOUR-DB. The selected odours are such that they (`rose`, `lemon`, `coffee`, `excrement`, `mint`) span the odour cube (see Fig. 2). Notice that the odours `rose`, `lemon`, `coffee`, `excrement` are closest to the odour components `fragrance`, `acidity`, `burntness`, `caprylicness` respectively and we choose `mint` to cover as much area in the total odour cube as possible (see Fig. 2). We trained a biometric system using EEGs from 5-odours (`rose`, `excrement`, `mint`, `coffee`, `lemon`) to model the subjects, and used EEG samples from the remaining 8 odours (3080 samples) for testing. Table IV shows that, a carefully selected set of 5 odours that span the odour cube, is able to model a subject very well. Notice that the performance of this biometric system for all combinations of feature sets and classifiers results in a performance in the range of 97.5 to 100%. It can be observed that the performance of Late fusion shows an absolute improvement of around 28% as compared to the best performing (`BioSPPy` features; RF classifier; 72.11%) randomly picked 5-odour biometric system (Table III).

We further reduced the number of odours used to model the subject to study the performance of the biometric system built with a smaller number of odours. The performance accuracies of 4, 3, 2, and 1 odours used to model the subject are captured in Table IV. We mention only the accuracies for the best odour combinations from the initially selected 5-odours. Note that the performance of the biometric system, in terms of accuracy, in Table IV is better compared to the performance of the biometric model using 12 odours (see Table II). We can observe that the performance accuracy drops by only 1% and 3% while using 4 (`rose`, `excrement`, `coffee`, `lemon`) and 3 (`rose`, `excrement`, `lemon`) odours, respectively, as compared to the system using 5-odour EEG data for training. We can observe that the best performance of a 1-odour biometric system trained on the `lemon` at 63.38% when `BioSPPy` features were used along with the RF classifier is much better

5-odour: `rose`, `excrement`, `mint`, `coffee`, `lemon`					
	`PyEEG`	`BioSPPy`	`PyWavelets`	Early	Late
SVM	98.18	98.80	98.67	98.90	99.35
RF	96.40	98.60	98.83	99.09	99.02
KNN	97.50	97.63	98.05	98.12	99.1
ANN	98.90	99.51	99.06	99.29	**100**
4-odour: `rose`, `excrement`, `coffee`, `lemon`					
SVM	97.58	97.09	95.50	95.96	98.29
RF	94.72	96.39	97.98	98.10	97.95
KNN	96.80	95.87	95.84	96.25	97.66
ANN	97.46	97.92	95.64	96.62	**98.90**
3-odour: `rose`, `excrement`, `lemon`					
SVM	93.14	89.90	90.13	92.54	92.73
RF	92.03	95.17	94.55	**97.16**	96.49
KNN	92.52	88.03	88.83	89.53	91.94
ANN	94.08	93.74	94.75	95.42	96.54
2-odour: `excrement`, `lemon`					
SVM	88.97	86.66	85.88	89.32	90.90
RF	92.73	92.82	93.22	**97.94**	94.85
KNN	87.53	84.37	85.95	87.10	89.75
ANN	89.89	91.71	89.14	93.19	93.03
1-odour: `lemon`					
SVM	54.85	52.23	52.86	54.35	52.98
RF	59.35	**63.38**	56.41	59.00	58.33
KNN	55.69	50.84	51.90	53.48	51.16
ANN	56.52	60.17	53.83	56.68	54.89

TABLE IV: Performance of 5,4,3,2,1-odour biometric systems.

than the best performance (57.84%) of 1-odour, randomly selected, biometric systems captured in Table III. However, the performance of 2-odour (`excrement`, `lemon`) biometric system is better than the 3-odour system; this requires further investigation. This set of experiments with a reduced number of odours to build a biometric system clearly demonstrates that a careful choice of odours, based on odour chemistry literature, can help build a usable biometric system for subject identification.

V. CONCLUSION

In this paper, we propose to use odour as a potential stimulus for EEG brainwave-based biometric identification. We also explore different sets of spectro-temporal features, intending to capture subject-specific characteristics for modeling the biometric system. The advantages of using odour over other conventional stimuli are: (1) some artifacts that reduce additional challenges of separating noise caused by the trigger from the actual brainwaves can be avoided, (2) odours provoke emotions related to strong memories attached to them, generate not only strong but also natural brainwave response. Rigorous experiments on a publicly-available dataset suggest that it is possible to build an odour-independent biometric system with very high-performance accuracy, using just 5 carefully chosen odours based on odour chemistry. More importantly, an odour-triggered EEG brainwave-based biometric system can be one of the best alternatives for people having severe damage to their physical structure because of accidents and cannot be authenticated using face, iris, audio, or finger-print biometric authentication systems.

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