# HASHING THE MAR COEFFICIENTS FROM EEG DATA FOR PERSON AUTHENTICATION

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## ABSTRACT

Electroencephalogram (EEG) recordings of brain waves have been shown to have unique pattern for each individual and thus have potential for biometric applications. In this paper, we propose an EEG feature extraction and hashing approach for person authentication. Multi-variate autoregressive (mAR) coefficients are extracted as features from multiple EEG channels and then hashed by using our recently proposed Fast Johnson-Lindenstrauss Transform (FJLT)-based hashing algorithm to obtain compact hash vectors. Based on the EEG hash vectors, a Naive Bayes probabilistic model is employed for person authentication. Our EEG hashing approach presents a fundamental departure from existing methods in EEGbiometry study. The promising results suggest that hashing may open new research directions and applications in the emerging EEGbased biometry area.

*Index Terms*— biometrics, electroencephalogram (EEG), hashing, dimension reduction, probabilistic algorithm

# 1. INTRODUCTION

Biometric technologies, referring to those that identify or verify the identity of a person using physiological (e.g. face and fingerprint) or behavioral characteristics (e.g., signature and voice), have the potential to solve many of the security problems. Traditional biometrics, such as facial patterns, fingerprints, eye irises, hand geometry and voice patterns, are well known for person authentication or identification purposes. Despite their widely used, such biometrics have certain limitations. For example, most of them are prone to forgery. This motivated researchers to study alternative biometric traits. It has been shown in previous studies that the brain-wave pattern for each individual is unique and thus can be used as a biometric [1]. The advantage of biometry from EEG is that it is almost impossible to duplicate human brain activity. Also, such electrophysiological biometric traits naturally allow aliveness detection to enhance the security of a traditional fingerprint-biometric-based system. Some potential application of EEG-biometry include building access control, secure information or multimedia access control.

To our knowledge, only a few works have been done in this emerging area of EEG-based biometry, mainly focusing on person identification. An identification system consists of two main components: EEG feature extraction and classification. Poulos et al.[2] introduced a method based on spectral analysis of EEG via the Fast Fourier Transform (FFT) and a neutral network classifier to identify individuals. Paranjape et al.[1] employed the autoregressive (AR) modeling of EEG from a single channel and applied discriminant functions to the AR coefficients for identification. Recently Palania et al[3] analyzed frequency powers in gamma band Visual Evoked potential as a biometric together with Elman Neutal Network. These studies are all for the purpose of person identification. Very recently, Marcel and Millan first proposed an EEG-based person authentication system[4], which uses the power spectrum densities as EEG features and propose a statistical framework based on a Gaussian Mixture model. It is worth mentioning that person identification and person authentication are two different types of applications and thus pose different challenges on decision making of biometry-based systems. The goal of person identification is to identify an individual from a group of persons (i.e. matching the biometric features of one person against all the records in a database), while the goal of person authentication is to confirm or deny an identity claim by a particular individual. We are particularly interested in person authentication in this paper.

We note that current research on EEG-biometry is characterized by directly modeling or classifying the extracted EEG features (e.g. AR coefficients). However, it is challenging to extract robust features. Also, since the dimension of the features used is generally huge, feature selection or reduction is an additional challenge for designing the classifiers or training the statistical models. Realizing that the problem of image authentication and our problem of person authentication share similar problem formulations and system requirements, to address these concerns, we propose a fundamental departure from the existing approaches in EEG-biometry area by investigating the EEG hashing direction for person authentication.

Image hashing, which is a content-based compact and exclusive feature descriptor of a specific image, has been proved to be a significant tool in multimedia security applications such as image authentication. Several hashing schemes based on dimension reduction techniques, including our Fast Jonson-Lindenstrauss Transform (FJLT)-based hashing algorithm proposed very recently, have been recently reported to provide superior performance. Motivated by the promising applications of the FJLT-based image hashing, in this paper, we present a FJLT-based EEG hashing scheme for person authentication. In Section 2, we first estimate the multivariate Autoregressive (mAR) coefficients as a feature set of EEG recordings, and then a dimension reduction technique FJLT is applied to hash the mAR coefficients from multiple EEG channels. In Section 3, we describe the EEG data set collected during motor tasks and present the results on person authentication when applying the proposed EEG hashing approach.

## 2. METHOD

### 2.1. The multivariate autoregressive model

A single channel autoregressive (AR) model can predict the current value of a time series from the previous observations of the same time series. A multivariate AR (mAR) model, however, is a model that for each value of one time series, the prediction depends not only on the history of the same time series but also the history of other time series. A mathematical formulation of mAR model is given as

$$x_1(n) = \sum_{i=1}^M a_{11}(i)x_1(n-i) + \dots \sum_{i=1}^M a_{1N}(i)x_N(n-i) + e_1(n)$$

$$x_N(n) = \sum_{i=1}^M a_{N1}(i)x_1(n-i) + \dots \sum_{i=1}^M a_{NN}(i)x_N(n-i) + e_N(n)$$
(1)

where N is the number of time sequences (channels),  $x_1(n) \dots x_N(n)$  represent the current values of each channel. M is the model order, indicating the number of previous data points used for prediction.  $a_{jk}(i)$ 's are mAR coefficients at delay i, and  $e_1(n), \dots, e_N(n)$  represent errors at time n which are modeled as uncorrelated random variables with zero mean. In a matrix form, we have the mAR model

$$\mathbf{x}(n) = \sum_{i=1}^{M} \mathbf{a}(i)\mathbf{x}(n-i) + \mathbf{e}(n).$$
(2)

Studies showed that there is particular functional connectivity between brain regions, mAR modleing of multi-channel EEG recordings is therefore encouraging, since mAR can capture information of the interactions between brain regions which can be used to enhance the discriminating power between individuals. Previous work using mAR coefficients as EEG features has been reported in neurology study, including work by Anderson [5] who extracted mAR coefficients from EEG as features used to discriminate different mental tasks. But very little or no work has been proposed using mAR coefficients from EEG for person authentication or person identification purposes.

Under the iid White Gaussian noise assumption, a robust mAR coefficient estimation can be obtained based on the least-square criteria (Please see the details in [6]).

#### 2.2. Fast Jonson-Lindenstrauss Transform

Although mAR coefficients are very informative, the dimension of the mAR coefficients extracted from EEG channels is very large. Hence, it is necessary for us to apply some dimension reduction techniques, especially in the case that the sample size is small. In this section, we introduce a recently developed dimension reduction technique that has been shown to be robust and time-efficient in image processing and other applications [7].

Johnson-Lindenstrauss lemma states that n points in Euclidean space can be projected down to  $k = O(\epsilon^{-2}log(n))$  dimensions while incurring a distortion within  $1 \pm \epsilon$  in their pairwise distance. where  $0 < \epsilon < 1$ . Based on this, Alion and Chazelle [8] proposed a new low-distortion embedding of  $l_2^{d}$  into  $l_p^{O(logn)}$ , called the Fast-Johnson-Lindenstrauss-Transform (FJLT), which is faster than standard random projections and easy to implement.

A FJLT  $\phi = FJLT(n, d, \epsilon)$  is a  $k \times d$  matrix, where d is the original dimension number of the original signal, k is a lower dimension number which is set to be  $c'\epsilon^{-2}log(n)$ , n is the number of data points,  $\epsilon$  is the distortion rate and c' is a positive constant real value. Suppose we employ the 4th order mAR model and estimate the mAR coefficients from 16 EEG channels, then the feature size is  $16 \times 16 \times 4$ . In this case we can consider the coefficients at each matrix as a data points, therefore n = 4 and M = 256. A Fast-Johnson-Lindenstrauss-Transform can be obtained by a product of three real valued matrices:

$$\phi = P \times H \times D,\tag{3}$$

where P and D are random and H is deterministic.

 P is a k-by-d matrix whose elements P<sub>ij</sub> are drawn independently according to the following distribution, where N(0, q<sup>-1</sup>) means a Normal distribution with zero-mean and variance q<sup>-1</sup>,

$$\begin{cases} P_{ij} \sim \mathcal{N}(0, q^{-1}) & \text{with probability} \quad q \\ P_{ij} = 0 & \text{with probability} \quad 1 - q \end{cases}$$

where

$$q = \min\left\{\frac{c\log^2 n}{d}, 1\right\},\,$$

for a large enough constant c.

• *H* is a *d*-by-*d* normalized Hadamard matrix with the elements as:

$$H_{ij} = d^{-\frac{1}{2}} (-1)^{\langle i-1, j-1 \rangle}, \tag{4}$$

where  $\langle i, j \rangle$  is the dot-product of the *m*-bit vectors i, j expressed in binary.

 D is a d-by-d diagonal matrix, where each diagonal element D<sub>ii</sub> is drawn independently from {-1,1} with probability 0.5.

With this kind of construction, we can get our intermediate hash(IH) by FJLT as

$$H = \phi(Feature) = P \times H \times D \times Feature.$$
(5)

Now the original feature vector is mapped into a lower dimensional space with small distortion. However, the size of our intermediate hash is still large. Consider again the 4th-order mAR model from a 16-channel EEG setting, the size of the original features in this case is  $256 \times 4$ . By setting  $\epsilon = 0.1$  and c = 0.72, we will end up with an *IH* with size  $100 \times 4$ . This problem can be solved by Random Weight Incorporation. Similar to the NMF-NMF-SQ hashing scheme proposed in[9], we introduce the pseudorandom weight vectors  $\{w_i\}_{i=1}^{M}$ , with  $w_i \in \mathbb{R}^k$ , and then calculate the final hash as

$$Hash = \{ \langle IH_1, w_1 \rangle, \langle IH_2, w_2 \rangle, ..., \langle IH_M, w_M \rangle \}, \quad (6)$$

where  $IH_i$  is the *i*-th column vector in IH and  $< IH_i$ ,  $w_i >$  is the inner product of  $IH_i$  and  $w_i$ . Note that the distance between the hash vectors  $IH_i$  and  $IH_j$  could be distorted by the weight vector, and hence degrades the classification performance. We sort the elements of  $IH_i$  and  $w_i$  in a descending order before the inner product and make sure a bigger weight will be assigned to a bigger component. By this operation, the perceptual quality of the hash vector is retained. Finally we end up with a hash vector with length M for the M-th order mAR model for EEG signals. This hash vector is very compact and robust, and can capture the essential features of the original mAR coefficients.

### 2.3. Authentication Decision

Due to its simplicity and generally good performance in real-world applications, we apply the naive Bayes model for decision making in our EEG person authentication system. Naive Bayes model is particularly attractive when the dimensionality of the feature variables is relatively high with respect to the sample size of the observations. Here we assume each element  $x_i$  of the hash vector X



**Fig. 1**. Location illustration of the EEG channels on the scalp. Those shaded are used for our experiments.

follows a Gaussian distribution and is statistically independent from each other. For each subject, we train a specific naive Bayes probabilistic model of the hash vector and further use the model for person authentication.

Based on the training data, we can estimate the parameters  $\theta$  of naive Bayes models by maximum likelihood estimation(MLE). Then the likelihood of a claim is calculated as

$$P(X|\theta) = \prod_{i=1}^{M} P(x_i|\theta_i), \tag{7}$$

where X is a calculated hash vector with length M.

The person authentication decision will be made as follow: given a threshold  $\tau$ , the claim is accepted if  $P(X|\theta) \geq \tau$  and otherwise rejected.

### 3. EXPERIMENTS AND RESULTS

# 3.1. EEG Database

The EEG data was collected from four normal subjects while performing motion related tasks. Subjects were seated about two meters away from a large screen, onto which a virtual environment (VE) was back-projected. The VE consisted of target and distracter balls rapidly approaching the subject. Subject were asked to interact with the VE display by 'blocking' virtual target balls. They were fitted with an EEG cap (CompumedicsR/NeuroscanR) recording signals from 19 electrodes. A illustration of the locations of EEG channels used is shown in Figure 1. EEG data from five tasks of this virtual reality experiment are collected and then used for person authentication. The trajectories of balls are different under the five tasks.

Raw EEG recordings are too noisy and should not be analyzed directly. A denoised EEG data set is obtained by subtracting the common reference from the EEG and EYE channels, then performing Independent Component Analysis(ICA). The raw data was collected at 1000Hz whereas the denoised data was obtained by downsampling the raw data to 250Hz and bandpassing it between 5-100Hz.

### 3.2. Feature Extraction and Hashing

The EEG signals from 16 channels out of the 19 channels were used for the analysis, as illustrated in of in Figure 1. The first step

**Table 1**. Mean and standard deviation of the hash value  $x_3$  from Task 1. S1 to S4 denote subject 1 to 4, respectively.

		3		1	5	
		S1	S2	S3	S4	-
	mean	95.3	129.0	63.0	167.8	-
	std	6.7	26.4	9.5	26.9	
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Fig. 2. Illustration of the separation of hash values between subjects.

is feature extraction by performing the 4-th order mAR modeling of the time series from 16 EEG channels. Then the mAR coefficients are hashed by the proposed FJLT hashing algorithm. Finally, we obtain a hash vector with length 4, which can be denoted as  $X = (x_1, x_2, x_3, x_4)$ . To indicate the differences between different subjects, in Table 1, we report the mean and standard deviation of  $x_3$  from seven subjects. We can see that they are located around different centers. To visually illustrate the separating differences of hash vectors from different subjects, Figure 2 shows a particular angle of the spatial plots of the first three hash values  $(x_1, x_2, x_3)$  from four subjects in Task 1. Points marked by different signs denote the trials of different subjects. Since the first three hash value are well separated already, the naive Bayes model based on all 4 hash values provides a good identification performance.

#### **3.3.** Experimental Results

Here we introduce two types of errors that are used for evaluating a person authentication system: False Rejection(FR), which occurs when the system refuses a true claimant, and False Acceptance(FA) which occurs when the system accepts an impostor. The performance is usually measured by False Rejection Rate(FRR) and False Acception Rate(FAR). The average of the two measures is called Half Total Error Rate(HTER). As described in Section 3.1, for each motor task we have 11 trials for each subject. We employ the leaveone-out cross validation approach in calculating the performance. Each time we train a client model using 10 out of the 11 trials and the left one trial of the client is used for testing. An impostor set is created by including 33 trials from the other 3 subjects. This process is repeated for each trial and for each subject. We heuristically setup a threshold for each subject. To demonstrate the performance of the proposed EEG authentication approach, Fig.3 shows one example of the log-likelihood (LL) values from one task based on crossvalidation, circles indicate the LL values from the client trials and the dots are for impostors. The FAR and FRR results based on cross



**Fig. 3**. The example Log-likelihood values of the EEG hash vectors from the client and impostors.

validation are given in Table 2. It is worth mentioning that a 9.1% of FAR in the table simply means that 1 out of 11 test trials is wrongly recognized.

The average HTER through five tasks and four subjects is 6.7% which is encouraging. In Marcel's work[4], they achieve an average HTER about 7.1%. Our results are at the same level of accuracy, though not fully comparable, since different EEG data sets are used.

## 4. CONCLUSION

This paper has studied the potential of hashing EEG features for person authentication. We proposed the use of Fast Johnson-Lindenstrauss Transform for robust EEG mAR coefficients hashing. We performed EEG experimental validation using a small group of normal subjects to show the potential of the proposed EEG hashing approach. Future work will include testing of our approach over a larger database with more clients and imposters and through different mental and motor tasks. Since, to our knowledge, there has been no work published in hashing of EEG features in the EEG-biometry area, this encourage us to explore hashing other EEG features, such as power spectrum densities, wavelet decompositions and so on. Also since the size of EEG features are often very large and the EEG trials is often with limited size, efficient dimension reduction techniques are crucial and worth further investigation in our study. We will examine other dimension reduction techniques for EEG hashing.

#### 5. ACKNOWLEDGMENTS

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**Table 2.** FAR,FRR and HTER in %. S1 to S4 denotes subject 1 to 4, and Average(S) is the average of 4 subjects.T1 to T5 denotes task 1 to 5 and Average(T) is the average of 5 tasks.

	S1	S2	S3	S4	Average(S)
FRR(T1)	0	0	0	9.1	2.3
FAR	7.2	3.03	10.8	7.4	7.2
HTER	3.58	1.52	5.4	8.26	4.7
FRR(T2)	9.1	9.1	9.1	9.1	9.1
FAR	8.54	4.1	9.3	3.0	6.2
HTER	8.82	6.6	9.2	6.0	7.6
FRR(T3)	0	0	9.1	9.1	4.5
FAR	3.0	5.2	7.1	9.3	6.2
HTER	1.5	2.6	8.1	9.2	5.3
FRR(T4)	9.1	9.1	9.1	9.1	9.1
FAR	2.7	6.1	8.9	10.5	7,1
HTER	5.9	7.6	9.0	9.8	8.1
FRR(T5)	9.1	9.1	9.1	0	6.8
FAR	6.6	4.5	7.2	7.6	6.5
HTER	7.9	6.8	8.2	3.8	6.7
FRR Average(T)	5.5	5.5	7.3	7.3	6.4
FAR	5.6	5.7	8.7	7.6	6.9
HTER	5.6	5.6	8.0	7.5	6.7

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