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EEG Feature Prediction from Tactile Data to Improve Object Shape Classification

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Abstract: In this work, we analyse the Electroencephalogram (EEG) and tactile signals acquired during dynamic exploration of objects of seven different geometric shapes and observe that classification performance using features from both the domains together is better than using the either alone. Classification is done by Support Vector Machine and Naïve Bayesian (NB) classifiers using discrete wavelet transform features. ReliefF algorithm is implemented for feature dimension reduction. A 6th order polynomial is fitted to tactile features to predict the EEG features which is helpful in cases where EEG data is unavailable. These predicted features recognize object shapes with improved classification accuracy when used with tactile features than using either of them separately. The results depict that object shape recognition rate using Naïve Bayesian classifier has been enhanced from 75.28% in case of tactile features to 82.63% for dimension reduced tactile features along with predicted EEG features.

Keywords: Electroencephalography, Discrete Wavelet Transform, Naïve Bayes, Polynomial Fitting, ReliefF, Support Vector Machine.

Introduction

Human brain responds to a wide variety of stimulus to perceive the world around us. Among these sensory stimuli, i.e. haptic perception occupies a very important role, allowing us to distinguish objects of varying shapes, sizes, surface texture, softness etc. As a consequence developing artificial hand with tactile sensors is a well-researched area in domains like rehabilitation, robotic surgery, tele-navigation and other Human-Computer Interaction (HCI) applications. The sense of touch can be perceived by analysing both brain and tactile signals obtained while exploring the objects around us. In EEG-based BCI, classification of brain responses has been studied for motor imagination [1], emotion recognition [2-3], visual perception [4], haptic perception [5], etc. In object shape recognition from tactile images is another wide area of re-search where methods like neural networks [6-7], image gradient [8], regional descriptors [9], etc. are used. After recognition, Markov models have been applied for 2-D shape reconstruction in [10].

In this work, the information obtained from both the sources is classified independently as well as simultaneously. These classification results indicate that fusing (concatenating) the information from both the sources provides better recognition than using the either source alone. EEG and tactile signals are acquired during dynamic exploration of the objects of seven different geometric shapes. These signals are decomposed using Discrete Wavelet Transform to obtain features for classification using Support Vector Machine (SVM) and Naïve Bayesian classifiers. The results validate our claim that using features from EEG and Tactile signals simultaneously produces better accuracy. Following this, we address two problems, first, the tactile and EEG signals generate a very high dimensional feature space which implies higher space complexity. This is tackled by reducing feature dimension using ReliefF algorithm. Secondly, tactually generated EEG signals are unavailable while using tactile sensor fitted artificial hand. This calls for an EEG feature prediction method, which is accomplished by using 6th order polynomial fitting. Classification accuracy with predicted EEG features is higher than that with dimension-reduced EEG features. This can be accounted for the reduction of the stochastic nature in the predicted EEG features than that in the original EEG features. The 'Methodology' section describes the major steps viz. pre-processing, feature extraction, dimension reduction, polynomial fitting and classification methods used in this work. Results are analysed in the 'Performance Analysis' section. Finally, 'Conclusion' section concludes the paper while mentioning future scope of research in this direction.

Methodology

This section briefly explains the experimental setup and the different steps taken during the course of the experimentation.

A. Data Acquisition

Experiments have been executed on 20 right-handed subjects (10 female and 10 male) in the age group 25±3 years. The stimulus consisted of a sequence of three segments each starting with an audio command: relax (for 2 seconds), explore (for 10 seconds) or stop (for 1 second). The subjects were blind-folded and were asked to explore each of the seven objects (Fig. 1) randomly provided (and recorded) by the experimenter. This provides unbiased non-overlapping responses. Each of the objects was explored 10 times by each subject, thus, providing a dataset of 20×10×7=1400 instances. EEG signal is acquired using Emotiv headset [11] having a sampling rate of 128Hz, from six channels viz. O1, O2, P7, P8, FC5 and FC6, positioned according to the International 10/20 EEG electrode placement [12]. Simultaneously, the tactile signal is acquired using PPS TactArray [13] which is a capacitive MEMS based pressure sensor consisting of a 32×32 grid of sensing elements having a sampling rate of 10.8Hz.

1 2 3 4 5 6 7

Figure 1. Different object shapes: 1-Cone, 2-Cube, 3-Cylinder, 4-Sphere, 5-Triangular Prism, 6-Hemisphere, 7-Hexagonal Cylinder

B. Pre-processing

EEG signals corresponding to tactile stimulus is found to have dominant spectral activity in 4-16 Hz. Thus the raw EEG signal is filtered using a 6th order elliptical band-pass filter of bandwidth 4-16 Hz. After temporal filtering, spatial filtering by common average referencing [12] (CAR) helps in removing the cross-talk from neighbouring electrodes. Finally, for EEG we have 6 time-series corresponding to each of these six channels and for tactile signals, we have 1024 time-series from each of the sensing elements of the 32×32 grid.

C. Feature Extraction

Wavelet Transform [14-15] yields time as well as frequency domain information of signal x[k] at multiple resolutions. In discrete domain, transformation is done by means of filters having pass-bands in different frequency ranges. The number of filter stages is indicated by the level of transformation. The energy distribution of the decomposed signals is given by Parseval's theorem (1). The first term on the right of (1) is composed of approximate coefficients $A_J[k]$ and the second term on the right of (1) is composed of detail coefficients $D_j[k]$. Signals are decomposed using 4^{th} order Daubechies (db4) waveform as the mother wavelet and the detail coefficients at level 4 and 5 (D4 and D5) are used as features.

$$\frac{1}{N}\sum_{k=1}^{N}\left(x[k]\right)^2=\frac{1}{N_J}\sum_{k}\left|A_J[k]\right|^2+\sum_{j=1}^{J}\left(\frac{1}{N_j}\sum_{k}\left|D_j[k]\right|^2\right) \quad (1)$$

In each of the cases, features of all the time series are horizontally concatenated. EEG signals yields a 792-dimensional feature vector whereas tactile signals produce a 23552-dimensional feature vector.

D. Dimension Reduction and Polynomial Fitting

The high dimensional feature space reserves a significant amount of resources. As a feature reduction technique, ReliefF algorithm [16] is implemented to reduce the feature dimension of both EEG and tactile feature spaces to 10. For every feature i, it selects a neighbourhood of k samples for every trial x_i in the dataset. A $nearHit_i$ is a sample from the same class and a $nearMiss_i$ is a sample from different class. Using the weight adaptation policy (2), weight of a feature increases if the second term of (2) is less than the third term and vice-versa i.e. a feature is more relevant if the samples of same class are numerically closer to each other than the samples of the different classes. 10 features with the highest weights (relevance) are selected. The value of k has been set at 3.

$$W_i=W_i-\left|x_i-nearHit_i\right|+\left|x_i-nearMiss_i\right| \quad (2)$$

The tactile features are used as independent parameter and the corresponding EEG features are fitted by polynomial fitting [17] for which polynomial of degree 2, 4, 6 and 8 is analysed. Later, the pre-fitted polynomial (polynomial coefficients) can be used to predict EEG features from tactile features. Root mean square error (RMSE) between the predicted and available EEG features is used as a performance metric for EEG feature prediction.

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E. Classification

Eight datasets are considered for classification: the original EEG dataset, the original tactile dataset, the original EEG and tactile dataset concatenated, the dimension reduced EEG dataset, the dimension reduced tactile dataset, the dimension reduced EEG and tactile dataset concatenated, the predicted EEG dataset, and the predicted EEG and the dimension reduced tactile dataset concatenated. Classification is done in a one-against-one framework using two classifiers (SVM [18] and Naïve Bayesian classifiers [19]). Train-set, validation-set and test-set are formed by randomly choosing 70%, 15% and 15% non-overlapping portions from each of the eight datasets. Train-sets are used to train the classifiers, validation-sets are used to choose the training parameters of features and classifiers, and test-sets are used to analyse the performance of the classifiers. Tuning the SVM implies selecting two parameters viz. cost for penalizing training errors (C) and margin between two classes (γ) are considered. C is varied from 40 to 200 in steps of 20 and γ is varied from 2 to 0.4 in steps of 0.2. After validation, best performance is noted with C as 100 and γ as 1. For the Naïve Bayesian (NB) classifier, the features are assumed to follow multivariate normal distribution whose mean and covariance are learned during the process of training.

Performance Analysis

The classification accuracies are averaged over all classes and all subjects and noted in Table I. As seen from these results, both the classifiers yield higher recognition rate with the EEG and tactile signal features taken simultaneously. Following this, the high feature dimension needs to be reduced and EEG features is required to be predicted using similar tactile features so that the accuracy enhancement hypothesis can be applied when the former is absent.

Table II presents the RMSE obtained during EEG feature prediction with polynomial of degree 2, 4, 6 and 8.As the degree of the polynomial increases beyond 6, the order of RMSE on validation-set is more than that on training-set indicating over-fitting. Thus, fitted polynomial of degree 6 is used in further work.

TABLE I. CLASSIFICATION ACCURACIES (%) WITH ORIGINAL DATASET

Classifiers	Original Dataset		
	EEG	Tactile	EEG+Tactile
SVM	56.4286	65.4762	67.5871
NB	57.1429	75.2381	76.9524

TABLE II. RMSE BETWEEN ORIGINAL EEG DWT FEATURES AND PREDICTED EEG DWT FEATURES

Polynomial Degree		2		4		6		8	
Dataset		T[1]	V[2]	T	V	T	V	T	V
Root Mean Square Error (RMSE)	F1,1[3]	0.2372	0.1763	0.2443	0.1930	0.3389	0.2599	0.3046	0.3429
	F2,2	0.2136	0.1846	0.2483	0.2858	0.3884	2.1459	0.6477	3.8656
	F3,3	0.2893	0.2957	0.3007	0.4293	0.3219	0.4955	0.8562	19.4832
	F4,4	0.2800	0.0703	0.2852	0.2925	1.6329	0.3448	3.5011	5.7218
	F5,5	0.2446	0.0723	0.3423	0.3783	0.2739	0.2282	2.1347	16.1019
	F6,6	0.3026	0.2694	0.4829	0.4037	0.6440	1.0652	1.2685	8.8474
	F7,7	0.2384	0.0612	0.2687	0.2928	0.2730	2.6636	1.8152	501.3364
	F8,8	0.2092	0.1658	0.2192	0.1585	0.2088	0.1848	0.3365	2.1203
	F9,9	0.2757	0.3732	0.3172	0.4999	5.4507	0.6968	192.2332	4.1877e+03
	F10,10	0.2077	0.2213	0.2216	0.6059	0.2070	0.2039	0.2367	42.2806

[1] Training Dataset (T): 70% of Original Dataset
[2] Validation Dataset (V): 15% of Original Dataset
[3] EEG feature 1 fitted to Tactile feature 1

The classifications results with the dimension reduced dataset and predicted dataset are shown in Table III. These results validates our claim of using predicted EEG features along with tactile features provides superior performance than using them disjointedly. In all the cases, we note NB classifier to perform better than SVM.

TABLE III. CLASSIFICATION ACCURACIES (%) WITH DIMENSION REDUCED AND PREDICTED DATASETS

Classifiers	Dimension Reduced Original Dataset			Predicted Dataset	
	EEG	Tactile	EEG+Tactile	EEG	EEG+Tactile
SVM	68.3333	76.1941	78.5714	73.5714	80.9048
NB	72.8571	78.7143	81.4286	73.3333	82.6302

Conclusion

This work aims at improving object shape recognition during tactile exploration. Seven geometric shapes are recognized from tactile and EEG signals and results support the hypothesis that the classification accuracy in case of joint EEG and tactile features is higher than that of either alone. By this method, we have improved object shape recognition rate from 75.28% (tactile features and NB classifier) to 82.63% (dimension reduced tactile features along with predicted EEG features and NB classifier). Thus our EEG feature prediction from the tactile features is an expedient choice where EEG signals are unavailable, which enhances the classification accuracy while reducing the computation cost as the features are dimension reduced. In future we will be incorporating non-linear approaches of EEG prediction. This may help in preserving the stochastic nature of EEG while resulting in more accurate object shape perception.

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Biographies

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