VARIABLE SUBSET SELECTION FOR BRAIN-COMPUTER INTERFACE

PCA-based Dimensionality Reduction and Feature Selection

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Abstract: A new formulation of principal component analysis (PCA) that considers group structure in the data is proposed as a Variable Subset Selection (VSS) method. Optimization of electrode channels is a key problem in brain-computer interfaces (BCI). BCI experiments generate large feature spaces compared to the sample size due to time limitations in EEG sessions. It is essential to understand the importance of the features in terms of physical electrode channels in order to design a high performance yet realistic BCI. The VSS produces a ranked list of original variables (electrode channels or features), according to their ability to discriminate between tasks. A linear discrimination analysis (LDA) classifier is applied to the selected variable subset. Evaluation of the VSS method using synthetic datasets selected more than 83% of relevant variables. Classification of imagery tasks using real BCI datasets resulted in less than 16% classification error.

1 INTRODUCTION

Brain-Computer Interfaces (BCI) enable people to control a device with their brain signals (Wolpaw et al., 2000). BCIs are expected to be a very useful tool for impaired people both in invasive and non-invasive implementations. Non-invasive BCI operation commonly uses electroencephalogram (EEG) from human brain for the ease of applicability in laboratory set ups as well as in patient applications. Datasets are generally high-dimensional, irrespective of the types of features (frequency band power, event-related desynchronization (ERD), movement-related potentials (MRP), event-related potentials (e.g. P300), etc.) extracted from EEG, if no previous knowledge about those features is considered. The low ratio of the number of samples to the number of variables is described as the curse of dimensionality (Duda et al., 2000). Frequently, in a BCI experiment, it is not easy to increase the number of samples to compensate for high-dimensionality. On the other hand, a variable subset calculation is feasible when few variables are relevant.

The variables in a dataset can be divided into irrelevant, weakly relevant and strongly relevant variables (John et al., 1994). A good subset should include all the strongly relevant variables and some of the weakly relevant ones. The variable subset to choose should minimize the generalization error (i.e. cross-validation error). Typically, the term 'feature' is used in the literature (Yu and Liu, 2004) instead of 'variable'. Nevertheless, we here use the latter to avoid confusion about the dimensions of the dataset (electrode channels) and the characteristic features (e.g. band power, MRP) extracted from EEG raw signals.

This work proposes a feature selection method based on a different formulation of Principal Component Analysis (PCA), introduced in (Dillon, 1989) that accommodates the group structure of the dataset. In the PCA framework, data dimensionality reduction methods typically use the selected principal components (PC) as a lower-dimensional representation of original variables, for discrimination purposes (Dillon et al., 1989; Kamrunnahar et al., 2008). However, the proposed work suggests that the dimensionality reduction should take place on the original variable space instead of the components, since it becomes more obvious which original variables are really relevant. The datasets from each subset of variables undergo

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linear discriminant analysis (LDA) for classification. The best subset in discriminating between task performances, for each subject, is evaluated by a cross-validation error.

We evaluated the proposed VSS method through both synthetic and real datasets. A synthetic dataset enabled us to evaluate this method in a controlled environment and simulated the 3 levels of variable relevance mentioned above. The real datasets were generated from movement-related potentials (MRP) as EEG responses to movement imagery tasks (Babiloni et al., 1999). Four subjects were submitted to these experiments and no subject had previous BCI experience. The lowest cross-validation error for each subject and the corresponding number of variables selected were assessed.

2 EXPERIMENTAL DESIGN

2.1 Symthetic Data

Among all variables p in the synthetic dataset, q relevant and p-q irrelevant Gaussian distributed variables were generated. All the generated variables had the same standard deviation σ. In order to best simulate a typical multivariate dataset, the relevant features were generated in pairs with correlation between variables. In this way, the variables are more discriminative if considered together. The first variable in each pair is considered as the predominant variable since its mean has distance d between groups. The distribution parameters were set similarly to (Lai et al., 2006). Pairs of correlated variables were generated until the quantity of relevant variables is reached. The remaining p-q variables (i.e. discrimination irrelevant) were generated from the same Gaussian distribution (no mean difference) for both groups. Four different datasets were generated with 80 samples: p=79 and q=6; p=79 and q=12; p=40 and q=6; p=40 and q=12. The first 2 datasets were intended to simulate the high dimensional/low sample size problem. The last 2 represent a lower high-dimensional space. The standard deviation σ was set to 2.5 in all datasets. The mean difference d was set to be equal to σ to simulate group overlapping. The values of both distribution parameters were set to best approximate the real variables extracted from the EEG data collected.

2.2 EEG Data

Four healthy human subjects, 25 to 32 years old, three males and one female, were submitted to 1 session each of motor imagery. The experiments were conducted under Institutional Review Board (IRB) approval at Penn State University.

Each session had 4 runs of 40 trials each. Each subject was instructed to perform one of 4 tasks in each trial. The tasks were tongue, feet, left hand and right hand movement imageries. The following 2 imagery task discrimination cases were considered for VSS algorithm evaluation: tongue vs. feet; left hand vs. right hand. After the first 2 s of each trial, a cue warned the subject to be prepared and 1 s later, a cue about the required mental task was presented to the subject. The subject was instructed to perform the task in the 4 s after the cue.

Data were acquired from 9 electrodes according to the standard 10-20 system (F3, Fz, F4, C3, Cz, C4, P3, Pz, P4). All electrodes were referenced to linked earlobes. Data were digitized at 256 Hz and passed through a 4th order 0.5-60 Hz band-pass filter. Each channel's raw EEG signal was epoched from the cue time point (0 s) to 4 s after the cue. The epoch was subdivided in 1 s time windows with no overlap (4 time windows). Each epoch was low-pass filtered at 4 Hz with an 8th order Chebyshev type I filter. Then, the filtered 256 points time series was down sampled to be 10 points long. The Matlab "decimate" function was used to accomplish both the filtering and down sampling. Only the 1^{st}-8^{th} data points of the resultant time series form the feature vector for each time window. The last 2 points of the time series were discarded because they seemed to be irrelevant on previous analyses. The feature matrix of each time window had 72 variables (8 features from each of the 9 electrodes) and 80 samples.

3 VARIABLE SUBSET SELECTION

The proposed VSS algorithm can be partitioned in 3 sequential procedures. Initially, the dataset dimensionality is reduced through a formulation of PCA that accommodates the group structure of the dataset (Dillon, 1989). Once the number of variables is reduced, the remaining variables are ranked according to their discrimination ability. Finally a cross-validation procedure is applied in order to determine the optimum subset of variables to select.

3.1 Dimensionality Reduction

The original feature matrix Y has samples in rows (n) and variables (p) in columns ($p < n$-1). The PCs are linear projections of the variables onto the orthogonal directions that best describe the dataset variance independent of any group structure that might be present in the data. Initially, the p PCs in $U_{n\times p}$ are calculated through singular value decomposition (SVD) of Y. Although the PCs are already organized by decreasing order of total variance accounted for, this order is optimized for orthogonality rather than discrimination between groups. In order to compensate for this and take the data group structure into account, the components should be ordered according to the across group variance (*AGV*) score (Dias, 2007), instead of the eigenvalues λ_i order that account for the total variance. The *AGV* score is used to rank each component in terms of the between group variance instead of the total variance. The AGV score is calculated according to (1) and its implementation is detailed in the appendix.

$$AGV_i = \frac{v^T_i \Psi_{Between} v_i}{\lambda_i} \quad (1)$$

$\Psi_{Between}$ represents the between group covariance matrix (see appendix for calculation details) and v_i represents the i[th] eigenvector of Ψ.

The dimensionality reduction results from the truncation of the component matrix (U), previously ordered according to the AGV scores. The truncation criterion was set to 80% (unless otherwise noted) of the cumulative sum (in decreasing order of the AGV scores) of every component's AGV. The truncated version of U ($U_{n\times k}$), with $k < p$ components, is a lower dimensional representation of the original variable space in Y and is often used as a reduced feature matrix (Kamrunnahar, 2008).

Although each component in U is a linear combination of all the original variables in Y, it is not always evident what each component means in the original variable space (Jolliffe, 2002). Hence, the original k variables ($Y_{n\times k}$) which have the most variance accounted for in the truncated component space ($U_{n\times k}$) are used as a representation of the original variable space Y. The vector *sub* keeps the indices of the k variables that were kept after this dimensionality reduction (see appendix for details).

Therefore, at the end of this stage, the dimensionality of the dataset has been reduced from p to k.

3.2 Variable Ranking

On the one hand, 2 different variables might have the same variance accounted for the k PCs but have different importance as discriminators (predictor in LDA). We indeed found in the current analyses, for both synthetic and real BCI datasets, that variables with high variance accounted for the k PCs were poor discriminators. On the other hand, a variable that is a good discriminator is expected to have high variance in the k PCs that were kept in the previous subsection. Therefore, in this 2[nd] procedure, a ranked list of the variables in *sub* is calculated according to their discrimination ability. The rank, in (2), computes the multivariate distance penalization observed when each variable at a time is removed from the subset of k variables.

$$rank(Y_j) = D - D_{-j} \quad , \ j \in sub \quad (2)$$

The multivariate distance D is calculated as in (3). M_1 and M_2 are the multivariate means of groups 1 and 2 respectively, and Ψ_k is the covariance matrix of the k selected variables. D_{-j} is calculated by excluding the variable j to calculate the multivariate distance.

$$D = \left[(M_1 - M_2)^T \Psi_k (M_1 - M_2) \right]^{1/2} \quad (3)$$

The output of this procedure is the reorganized version of *sub* with variables in descending order according to $rank(Y_j)$.

In order to show the importance of the dimensionality reduction step in eliminating non-relevant variables, all the p variables in Y were ranked and classified in a separate cross-validation step where the 1[st] procedure (i.e. dimensionality reduction) was omitted (figures 1 and 3).

3.3 Cross-Validation

Once the subset of variables *sub* is ordered according to (2), an LDA classifier is applied iteratively on each feature matrix $Y_{sub(f)}$ containing the f top most ranked variables in *sub,* for f=1,…,k. The leave-one-out error rate (LOOR) is calculated in each iteration. The lowest LOOR value achieved determines which subset of variables *opt* (*opt* $\subset$ *sub*) is optimal according to this approach (results in figures 1 and 3).

A different approach of Fisher Discriminant Analysis (Schiff, 2005) that was robust on spatiotemporal EEG pattern discrimination was applied. The canonical discrimination functions Z_i are the result of a linear transformation of original data Y according to (4). The discrimination coefficients of each i^{th} canonical discrimination function are denoted by the columns of b_i^T.

$$Z_i = Y_{sub(j)} b_i^T \tag{4}$$

The group membership prediction was based on the posterior probability π_{gz} as the probability that the data of a given value z came from group g (Dias, 2007). The highest π_{gz} value ($g \in \{1,2\}$: only left vs. right hand movements and tongue protrusion vs. feet movement imagery discriminations were assessed) was the predicted group membership for posterior calculations.

The discrimination quality was assessed by LOOR and Wilks' statistic W. Further details on the classification method can be found in (Dias, 2007).

4 RESULTS

The feature selection process on the synthetic data was evaluated for 4 different cases of number of features p and different number of relevant features q. Two cases are illustrated in figure 1. The 1st case (p=40; q=6) at figure 1 left plot achieved 7.5 % of LOOR and Wilks' statistic W=0.33 which is very significant since the 99 % confidence value $W99$ (W is chi-squared distributed with $p \times (n-1)$ degrees of freedom) for this statistic is 0.74. All 6 relevant variables were selected for the optimal subset (minimum LOOR). The 2nd case (p=40; q=12) achieved 0 % LOOR for 10 variables (10 relevant features out of 12 were selected and all the predominant ones were selected) and W=0.16 ($W99$=0.75). The 3rd case (p=79; q=6) at figure 1 right plot reached 3.7 % LOOR for 5 variables (all the predominant variables were selected) and W=0.23 ($W99$=0.83). Finally the 4th case (p=79; q=12) reached 3.7% LOOR for 14 variables (all relevant variables were selected plus 2 irrelevant ones) and W=0.14 ($W99$=0.69).

The FSS algorithm was also tested in real data from 4 subjects which achieved between 11.4 % and 29.1 % LOOR (each subject's best time window) for left vs. right imagery (figure 2 left plot). During tongue vs. feet imagery performance, the LOOR was between 15.2 % and 30.4 % (0-1 s time window), as seen on figure 2. The best occurrence from each discrimination case is depicted on figure 3. In both cases 4 variables were selected as the optimal subset. In JF's left vs. right performance (figure 3 left plot) analyses, features from C4, Pz, F3 and Fz channels were selected. In JI's tongue vs. feet performance (figure 3 right plot) analyses, features from P3, C3, Cz and Pz channels were selected. On figure 1 as well as figure 3, the variables selected until the minimum LOOR is reached (opt) are considered relevant and all the following variables selected are considered irrelevant.

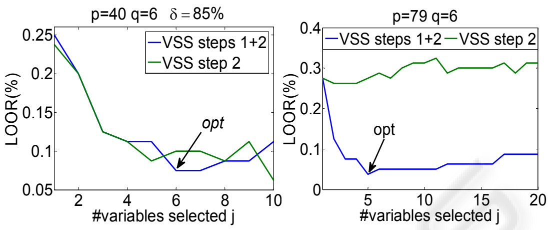

Figure 1: Plots of LOOR vs. number of variables selected from sub for both the VSS algorithm (blue line) and VSS 2nd step separately (green line). Two different cases were illustrated for q relevant variables out of p variables.

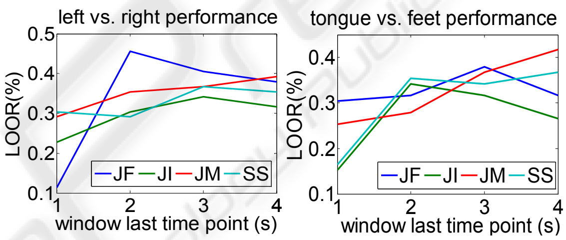

Figure 2: LOOR variation through 4 time windows (1-4 s after cue) for all 4 subjects (JF, JI, JM and SS) for left vs. right movement imagery performance (left plot) and tongue vs. feet movement imagery performance (right plot).

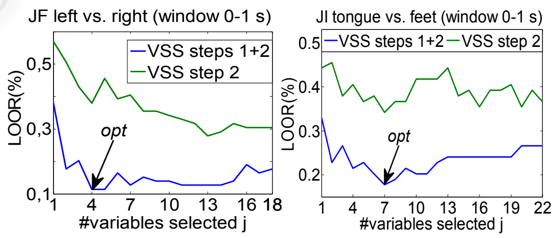

Figure 3: LOOR vs. number of variables selected for JF (left plot) and JI (right plot) in time window 1.

5 DISCUSSION AND CONCLUSIONS

The goal of this VSS approach is to find few relevant variables for discrimination in a high-dimensional variable space. The results with synthetic datasets reveal that this goal is feasible: at least 83% of the relevant variables were selected for the optimal subsets; 100% of the predominant variables were selected for all optimal subsets; all the discriminations reached less than 7.5% LOOR and were very significant. The 1st and 2nd cases show that this approach is also applicable for lower dimensional variable spaces (p=40;N=80) as well as high-dimensional ones (3rd and 4th cases). As shown in figure 1 for p=79 and figure 3 the LOOR is much larger when only the 2nd step of VSS is applied alone (green line) to all original variables, than the LOOR achieved when both steps are applied jointly (blue line). Although the LOOR increase in the absence of the 1st step is less evident for p=40 (figure 1), the optimal solution is still achieved when both steps are applied jointly. Therefore, it can be concluded from these results that the proposed algorithm reduces the number of variables efficiently as well as decreases the discrimination error.

Real BCI data results, on figure 2, show three good discrimination cases (LOOR lower than 16%) for three different subjects. The presence of just few relevant variables in these BCI datasets seems likely once 4 (subject JF) and 7 (subject JI) variables out of 72 were selected for the optimal subset in figure 3. As suggested in the literature (Babiloni, 1999), for all cases but one in figure 2, the best time window for classification appears to be the first second after cue.

Our findings show a novel mean to down-select variables in BCI that accomplishes both discriminative power and dimensionality reduction. Such a strategy is valuable in decreasing the computational complexity of neural prosthetic applications.

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APPENDIX

This section details the dimensionality reduction implemented on the proposed variable selection algorithm. The algorithm presented on the bottom of this section enumerates every command of this procedure.

On the line 1 of the algorithm, Y is decomposed through SVD into 3 matrices: $U_{n\times p}$ (component orthogonal matrix), $S_{p\times p}$ (singular value diagonal matrix) and $V_{p\times p}$ (eigenvector orthogonal matrix). The eigenvalues vector λ is calculated on line 2 as the diagonal of S^2. The AGV score is calculated for every PC through lines 4 to 6.

Once it is considered that both groups to discriminate have the same covariance matrix, the pooled covariance matrix should be calculated as the within group covariance matrix Ψ_{Within}:

$$\Psi_{Within} = (n_1 - 1)\Psi_1 + (n_2 - 1)\Psi_2 / n_1 - n_2 - 2$$

Ψ_i and n_i are respectively the covariance matrix and number of samples belonging to the i^{th} group.

Considering Ψ as the total covariance matrix, the between groups covariance matrix $\Psi_{Between}$ is calculated as:

$$\Psi_{Between} = \Psi - \Psi_{Within}$$

On line 7, the vector *rAGV* is a version of *AGV* in descending order. On lines 8 and 9, λ and the columns of *V* are similarly reordered in $r\lambda$ and *rV* respectively, to match *rAGV*. Note that *AGV* is originally ordered according to the descending order of the eigenvalues λ_i (line 5). The reordered *AGV* indices are kept in *dpc,* which stands for 'discriminative PCs', where $rAGV=AGV_{dpc}$.

Each component's percentage of the sum of all *AGV* scores is calculated on line 10. The number of components *k* out of *p* to maintain determines the truncation to be performed in *U*. *k* is calculated on line 11 as the number of elements of *%rAGV* whose cumulative sum is higher than the component selection criterion (δ).

Considering the spectral decomposition property of the covariance matrix:

$$\Psi = \sum_{i=1}^{p} \lambda_i v_i v_i^T$$

The columns of *V* are the eigenvectors v_i. The diagonal values of Ψ give the variance of the variables in *Y* accounted for the *p* PCs, as well as $TruncVar_j$ gives the 'truncated' variance of variable *j* accounted for the *k* PCs that were kept for dimensionality reduction.

On lines 15 and 16, the vector *rTruncVar* is a descending ordered version of *TruncVar* and the indices of the *k* top most variables in *rTruncVar* are copied into the subset of variables *sub.*

```
Input Data: Y, Ψ_BETWEEN, δ
Output Data: sub
   1. [U,S,V^T] = SVD(Y);
   2. λ = diag(S^2);
   3. p = # columns of Y;
   4. for i=1 to p do
   5.      AGV_i = V_i^T×Ψ_BETWEEN×V_i/λ_i
   6. end for
   7. [rAGV,dpc] = sort AGV in
      descending order
   8. rλ = λ_dpc {λ is reordered to
      match rAGV}
   9. rV = V_dpc {V is reordered to
      match rAGV}
   10. %rAGV = 100*rAGV / Σ_{i=1,..,p} rAGV_i
   11. k = number of first %rAGV
       elements whose cumulative sum > δ
   12. for j=1 to p do
   13.     TruncVar_j = Σ_{i=1,..,k} rλ_i×rV_ji^2
   14. end for
   15. [rTruncVar,Index] = sort
       TruncVar in descending order
   16. sub = 1st k elements in Index
```