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Statistical Modelling of EEG Data for Hand Movement

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ABSTRACT:
Brain machine Interface (BMI) improves the approach to life of traditional individuals by enhancing their performance levels. It additionally provides approach of communication for the disable individuals with their encompassing United Nations agency ar otherwise unable to physically communicate.BCI is use to regulate computers, robots, prosthetic devices and alternative helpful technologies for rehabilitation. The dataset used for this study has been obtained from the BCI competition. Once pre-processing of the signals from their electrodes (C3 & C4), the rippling coefficients, Power Spectral Density of the alpha and also the central beta band and also the average power of the individual bands are utilized as options for classification. In one amongst the approaches we have a tendency to feed all the extracted options singly and within the alternative approach we have a tendency to thought of all options along and submitted them to LDA, QDA and KNN algorithms clearly to classify left and right limb movement. The aim of this study is to research the performance of linear discriminant analysis (LDA), quadratic discriminant analysis (QDA) and K-nearest neighbor (KNN) algorithms in differentiating the raw EEG knowledge obtained, into their associative movement, namely, left-right movement additionally the importance of the feature vectors elite is highlighted during this study. the overall set to feature vector comprising all the options (i.e., rippling coefficients, PSD and average band power estimate) performed higher with the classifiers while not a lot of deviation within the classification accuracy, i.e., 80%, 80% and 75.71% with LDA, QDA and KNN severally rippling coefficients performed best with QDA classifier with Associate in Nursing accuracy of eightieth. PSD vector resulted in superior performance of eighty one.43% with each QDA and KNN. Average band power estimate vector showed highest accuracy of eighty four.29% with KNN algorithmic program. Our approach bestowed during this paper is sort of easy, straightforward to execute and is valid robustly with an outsized dataset.

Keywords: Bel, ERS, ERD, wavelet coefficients, PSD, average band power estimates, LDA, QDA, KNN

I. Introduction

Controlling a laptop or robotic device with thought solely with none physical intervention is that the principal plan behind brain laptop interfaces (BCI). BCIs use communication of the brain with outer atmosphere that does not follow brain\'s standard output pathways (i.e., through peripheral nerves and muscles). The brain activities for BCI is measured victimisation graphical record (electroencephalography), ECoG (electrocorticography), fNIRs (functional close to Infrared spectroscopes), fMRI (functional resonance Imaging), one thousand (magneto encephalography), LPF (Local Potential Field) [3]. Graphical record primarily based BCI is most popular because it is noninvasive, value economical, portable, and easy-to-use and provides superior temporal resolution. BCIs not solely improve the approach to life of the conventional folks by enhancing their performance levels, it conjointly provides how of communication for the disabled folks with their encompassing United Nations agency are otherwise unable to physically communicate. BCI is accustomed management computers, robots, prosthetic devices and alternative helpful technologies for rehabilitation. Capturing motor intention and corporal punishment the specified movement are the first basis of brain-computer interfaces for neural medical specialty. They restore the motor ability or communication to impaired people by decryption the intentions of the individual. One in every of the most analysis areas of graphical record primarily based BCI for control is to decrypt the brain signals cherish explicit limb movements [1], [2]. it\'s currently quick changing into a replacement tool for communication, and might be employed in sectors like artificial intelligence, mass communication, vehicles, games and recreation.

The aim of this study is to research the performance of linear discriminant analysis (LDA), quadratic discriminant analysis (QDA) and K-nearest neighbor (KNN) algorithms in differentiating the raw graphical record knowledge obtained, into their associative movement, namely, left/right hand movement. Co-jointly the importance of the feature vectors hand-picked is highlighted during this study. Filtering is performed on the graphical record signals to create them free from noise, and afterwards feature extraction and classification are performed. The options thought-about during this paper embrace rippling coefficients, average band power and power spectral density. The raw dataset has been de-noised by filtering, followed by feature extraction by rippling transformation, band power estimation and power spectral density strategies. In one in every of the approaches we tend to fed all the extracted options severally and within the alternative approach we tend to fed all the extracted options to LDA, QDA and KNN classifiers clearly to classify left and right limb movement (Fig. I).

During imagination or execution of part movements, an incident connected synchronization (ERS) within the gamma band and an incident connected desynchronization (ERD) within the alphabetic character and beta band of the encephalogram originates in our brain. The gamma ERS and therefore the mu-beta ERD happens at the contralateral aspect of the brain close to sensory system and motor {area motor, region area, excitable area, cortical area, cortical region} area throughout explicit limb movement. Just in case of ERS the ability of the gamma part will increase, whereas just in case of ERD the ability of the mu-beta part decreases. [4], [5].

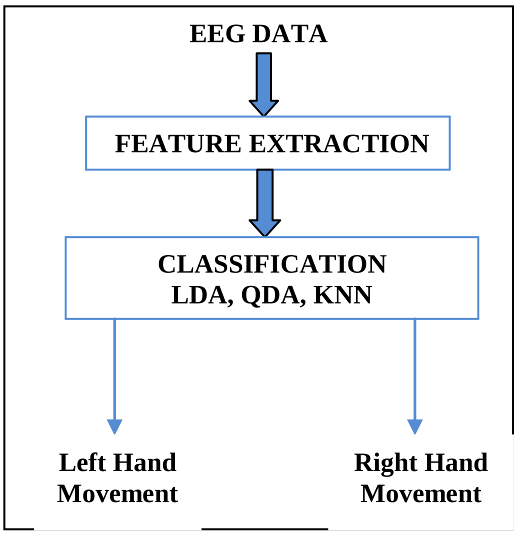

Fig.1: Block diagram of the approach applied in this paper

II. Experimental Data Description

The experimental information was obtained from BCI Competition 2003 provided by Department of Medical information processing, Institute for medical specialty Engineering, University of Technology city. This dataset was recorded from a traditional subject (female, twenty five yr) throughout a feedback session wherever the topic was created to sit down in an exceedingly quiet chair with armrests. The task was to regulate a feedback bar by suggests that of images left right movement within which the order of left and right causes were random. The recording was created employing a G.tec electronic equipment and a Ag/ AgCI conductor and 3 bipolar graph channels were measured over C3, CZ and C4 conductor (Fig.2). The experiment consists of seven sessions with in trials each conducted on an equivalent day with many minutes break m between. In every trial, the first two seconds was quite within the two second AN acoustic information indicates the start of the path with a fixation cross \'+\' displayed on the screen and at the third second the visual cue (left-right arrow) is displayed. At an equivalent time the topic was asked to maneuver the bar within the direction of the cue as feedback. The feedback was supported river parameters of channel C3 and C4 and therefore the river parameters were combined with a discriminant analysis into one output parameter (Fig.3). The graph information was sampled at 128Hz.

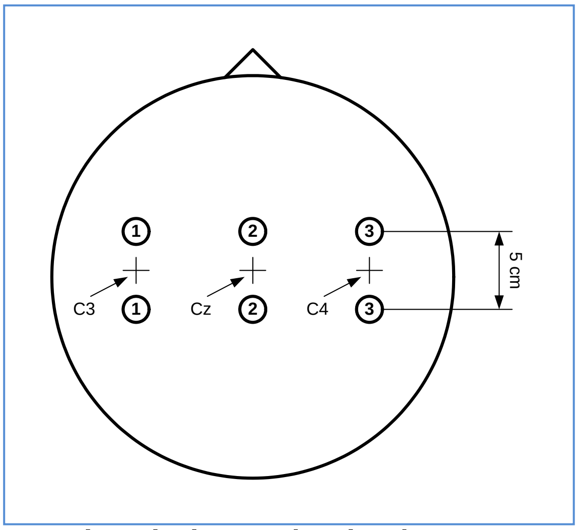

Fig.2: Electrode placement based on the experiment

III. Pre-Processing Of The Experimental Data

A total of 280 trials got of nine second every. Out of the 3 electrodes used, C3 and C4 are light for this study. CZ is not noted as a result of it's of very little connection for extracting info on left-right movement [6].

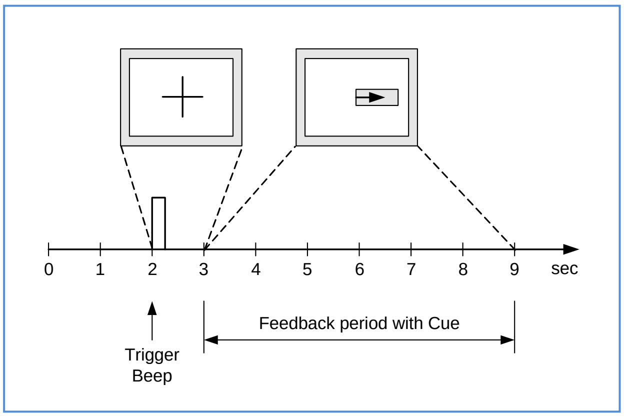

Fig.3: Timing scheme of the experiment

Thus, the full dataset comprised of 1152 x two x 280 information. The trials for training and testing were elite at random to forestall any systematic result owing to feedback. So, a complete of a hundred and forty trials were elite for coaching and also the rest a hundred and forty trials for take a look at because the visual cue started from t=3 sec to t=9 sec, thus, solely the information for this point interval was elite. Currently it's famous that the brain electrical activities principally occur within the zero.3-40Hz bands, and also the higher frequencies will be thought-about as noise supported their environments and recording techniques. Therefore a band pass filter is employed to filter within the frequency band: zero.5-30 Hz.

IV description of the features extracted

A. Wavelet Features Feature Extraction

Wavelet transforms may be a terribly effective thanks to extract options from AN encephalogram signal [7,8]. Their ability to discriminate each the temporal and spectral domain options of the signals makes them a vital quality for encephalogram analysis. conjointly the ripple remodel don\'t suffer from the time-frequency trade off inherent in brief Time Fourier remodel (STFT) and Fourier remodel (FT) as their multi-scale approximation permits for effective localization of the signal with numerous spectral-temporal characteristics. so for a non-stationary signal like encephalogram, it\'s a good analysis tool. The distinct ripple transforms analyzes the signals at totally different resolutions by rotten the signal into coarse approximation and detail info. Every level includes of 2 digital filters and 2 down-samplers by a pair of. The down-sampled outputs of the first high-pass and low-pass filters provides the detail D one and approximation AI, severally. The primary approximation is any rotten and therefore the method continued, till the specified result\'s obtained. [9, 10].

In the gift study, Daubechies (db) mother ripple of order four is employed. Once trials with the encephalogram knowledge, the D3 options i.e., the third level constant for the individual electrodes were elite collectively of the feature parts for the [mal feature vector. Figure four and five shows the ripple decomposition for left-right representational process for C3 and C4 conductor.

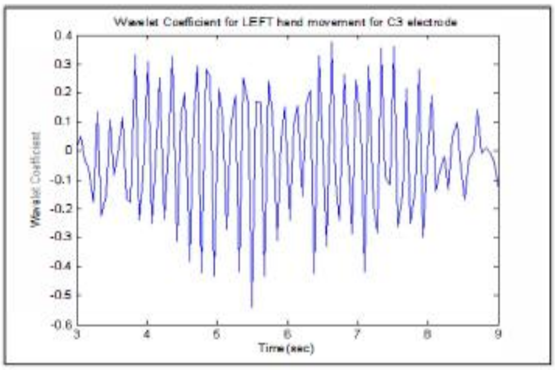

Fig.4a: Wavelet Coefficient for Left movement for C3 electrode

Spectral density ways extract info from a sign to explain the distribution of its power within the frequency domain. the ability spectral density (PSD) is outlined because the Fourier remodel (FT) of the signal's autocorrelation perform only if the signal is stationary in an exceedingly wide sense [10]. So for AN encephalogram signal segmenting the entire statistic knowledge would be a perfect approach. For this paper, the Welch approach was applied together with a performing window of length sixty four. The Welch methodology divides the day series knowledge into overlapping segments, computing a changed periodogram of every section and so the PSD estimates is averaged.

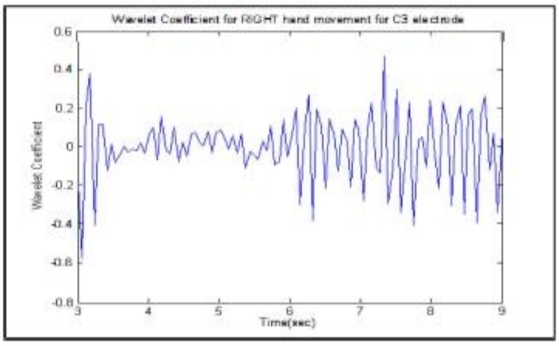

Fig. 4b: Wavelet Coefficient for Left movement for C3 electrode

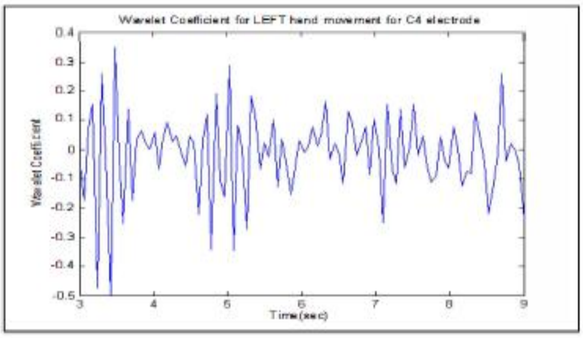

Fig.5a: Wavelet Coefficient for Left movement for C4 electrode

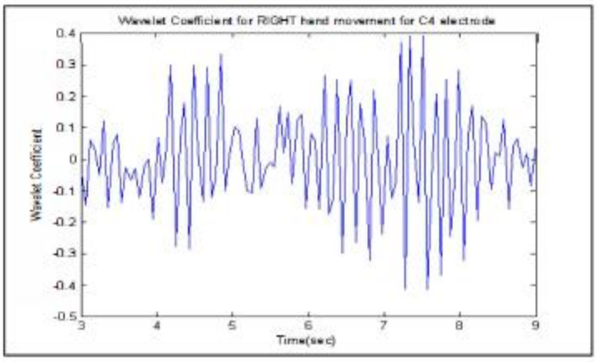

Fig.5b: Wavelet Coefficient for Left movement for C4 electrode.

B. Spectral Estimation Method

The PSD estimates were obtained for two frequency bands, namely the alpha or mu band (8-12Hz) and the central beta band (I8-25Hz) for each respective electrode. Also the average power was obtained for each band. Then the difference of the PSD estimates (formula 1) and average power (formula 2) is selected as another feature for this study.

$$F_{PSD} = \sum_{f=a}^{b} PSD_{C4}(f) - \sum_{f=a}^{b} PSD_{C3}(f)$$

…….. (1)

$$F_{POW} = POW_{C4} - POW_{C3}$$

………. (2)

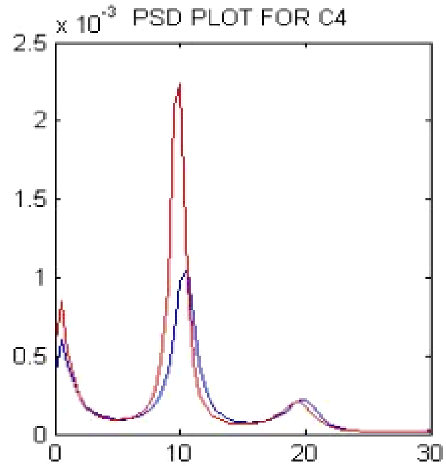

Fig. 6a: PSD plot for Electrode C4

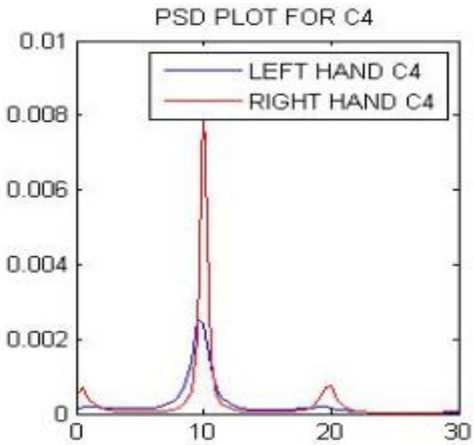

Fig. 6b: PSD plot for Electrode C4

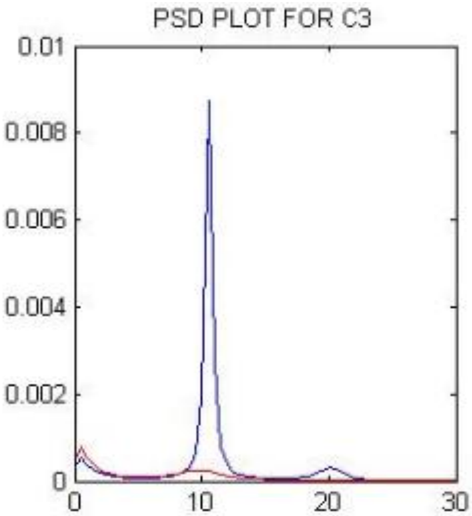

Fig. 7a: PSD plot for Electrode C3

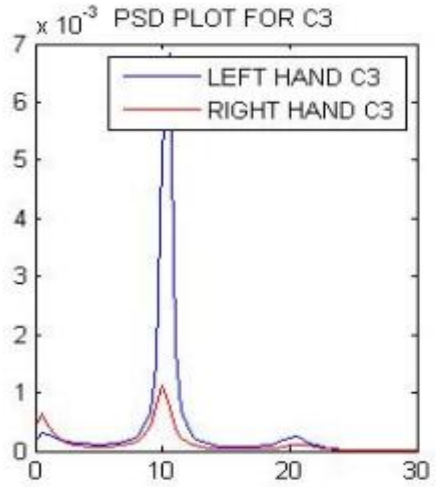

Fig. 7b: PSD plot for Electrode C3

TABLE I. FEATURE VECTORS WITH THEIR RESPECTIVE SIZE

FEATURED VECTORS	SIZE (NO. of features per trials X No. of Trials)
Wavelet Coefficient (D3)	204 x 140
Alpha band PSD Estimates	768 x 140
Alpha band Average Power	1 x 140
Beta Band PSD estimates	768 x 140
Beta Band Average Power	1 x 140
Total	1742 40

V. Results And Discussions

The take a look at knowledge was used for validation of the classifiers. truth labels of the take a look at knowledge were obtained from the web site of the BCI competition 2003. All of the information were band pass filtered between the frequency ranges of zero.5-30Hz. From the 2 electrodes of interest, namely, C3 and C4, rippling coefficients, PSD estimates for the alpha and beta bands and their corresponding powers were elite because the options for this study. The feature vectors are valid victimization paired t-test and their various likelihood of the prevalence of sort I and kind II error area unit shown in Table II. every single feature vector and also the complete feature set were fed into LDA, QDA and KNN classifiers on an individual basis during a MA TLAB atmosphere. The results of the classification area unit shown in Table II. The error in Table II provides the misclassification error whereas coaching the dataset and also the accuracy is obtained once the take a look at knowledge is fed to the trained classifier. Fig seven illustrates the accuracy with completely different range of options for the 3 classifiers. it\'s seen that the accuracy is almost an equivalent for the various range of options taken. it's additionally ascertained from Table II that once solely the rippling constant feature vector is employed, it gave poor classification accuracy with the classifiers (i.e., LDA, QDA and KNN) thanks to its complete non dimensionality rippling coefficients classification with QDA showed highest accuracy of eightieth. The facility spectral density estimate feature vector showed higher classification accuracy with relation to rippling coefficients and average band power estimates. The complete feature vector set comprising all the extracted options with bigger spatial property indicated higher performance accuracy of eightieth, 80% and 75.71% with LDA, QDA and KNN severally. LDA showed higher classification with PSD vector And complete feature set with an accuracy of eightieth. QDA performed higher with PSD vector with AN accuracy of eighty one.43%. KNN showed highest performance with average band power estimate vector with AN accuracy of eighty four.29%.

Table Ii Result Of Class1f1cation Ith The Selected Features

FEATURES	TYPE I ERROR	TYPE II ERROR	CLASSIFIER	ERROR (IN %)	ACCURACY (IN %)
Wavelet Coefficient	0.05	0.1943	LDA QDA KNN	35.71 8.57 34.29	48.57 80 65.71
Power Spectral Density	0.05	0.0223	LDA QDA KNN	20 20.71 13.57	80 81.43 81.43
Average band power	0.05	0.0245	LDA QDA KNN	19.29 19.29 12.86	78.57 77.86 84.29
All	0.05	0.0008	LDA QDA KNN	19.29 20.71 12.14	80 80 75.71

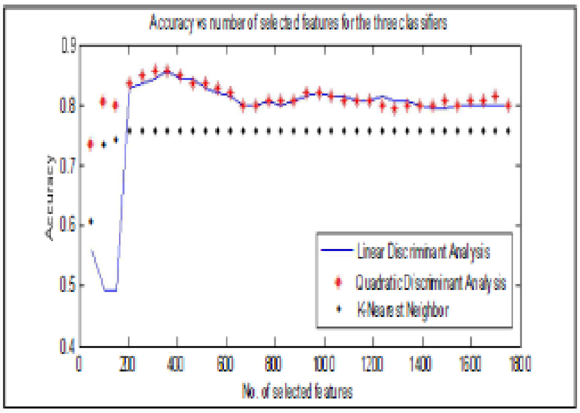

Fig.9: Beta Band PSD estimate for a) left movement b) right movement

VI. Conclusion

In this paper, options are extracted from the preprocessed graph signal and fed to the motor mental imagery classifiers for differentiating the graph signal to its corresponding left-right limb movement rippling remodel, power spectral density estimate and average band power estimates are techniques followed during this study for feature extraction. In one in all the approaches we have a tendency to feed all the extracted options on an individual basis and in another approach we have a tendency to shape a feature vector and fed it to LDA, QDA and KNN algorithms clearly to classify left and right limb movement. it\'s evident from the results that thanks to the non-linearity of the rippling coefficients it contributed to poor classification accuracy once used on an individual basis once every feature vector is fed for classification, PSD showed highest accuracy than the remainder feature vectors. the whole set to feature vector comprising all the options (i.e., rippling coefficients, PSD and average band power estimate) performed higher with the classifiers while not a lot of deviation within the classification accuracy. Plenty of the classification depends on the method of the feature vectors hand-picked and therefore the parameters that outline these vectors. The process of the options needs additional validation and study to boost the accuracy of the classifiers. Also, it\'s command that the mix of feature vector is important for correct classification, so newer options ought to be tried bent on additional improve the classification of left-right motor mental imagery. Our approach of feature extraction and classification given here is incredibly easy and strong to manage graph primarily based BCI devices it\'s needed to find out additional relevant options with less procedure time and with higher procedure potency. Future study during this direction can aim at techniques for optimizing feature choice, extraction and classification methodologies to be enforced in on-line classification of graph information for BCI analysis.

References

[I] Schwartz A.B., Cui X.T., Weber DJ., Moran D.W. "Brain Controlled Interfaces: Movement Restoration using Neural Prosthetics." Neuron vol. 52, October 2006, pp. 205-220

[2] Lebedev M.A., Nicoleis, "Brain-machine interface: Past, present and future", Trends Neurosci. Vol. 29(9), September 2006, pp.536-546

[3] Anderson R.A., Musallam S., Pesaran B., "Selecting the signals for a brain-machine interface", Curr Opin Neurobiol Vol.l4 (6), December 2004, pp.720-726

[4] Matsunanga T., Katayama Y., Hayami T., Iramina K. "Measurement of mulbeta ERD and gamma ERS during the imagination of body parts movement." 30'h Annual International IEEE EMBS Conference Vancouver Canada, August 2008

[5] Hema C.R., Paulraj M.P., Yaacob S., Adorn AH., Nagarajan R. "Recognition of motor imagery of hand movements for a BMI using PCA features." 2008 international Conference on Electronic Design, Penang, Malaysia, December 2008

[6] Xu Huaiyu, Lou Jian, Su Ruidan, Zhang Erpang "Feature Extraction and Classification of EEG for imaging left-right hands movement."

[7] Schloegl A, "Dynamic spectral analysis based on an autoregressive model with time-varying coefficients", IEEEEMBC and CMBEC, 1995

[8] Darvishi S., AI-Ani A "Brain-computer interface analysis using continuous wavelet transform and adaptive neuro-fuzzy classifier", Proc. 291h Int. Annu. Conf. IEEE Eng. Med. BioI. Soc., August 2007, pp. 3220-3223

[9] XU Q., Zhou H., Wang Y., Huang J. "Fuzzy support vector machine for classification of EEG signals using wavelet based features." Medical Engineering & Physics 31, 2009, pp. 858-865

[10] Herman P., Prasad G., McGinnity T.M., Coyle D. "Comparative analysis of spectral approaches to feature extraction for EEG-based motor imagery classification." IEEE Trans. Neural sys. Rehab eng. 16(4), August 2008, pp. 317-326

[11] Daniella Birkel, "Regularized Discriminant Analysis"