6. Workshop Automatisierungstechnische Verfahren für die Medizin vom 24.-25. März 2006 in Rostock-Warnemünde

„Dimension reduction effect on EMG signal identification using MLP, RBF and LVQ methods in case of relevant features“

A. Zeghbib, F. Palis
Otto-Von-Guericke Universität, Magdeburg, Deutschland

T. Schauer, R. C. Salbert
Max-Plank-Institut für Dynamik Komplexer Technischer Systeme, Magdeburg, Deutschland

Band:	Abstracts der Vorträge des 6. Workshops der Automed 2006
Editors:	T. Ellerbrock
ISBN:	3-86009-296-0
Pages:	87-88

Dimension reduction effect on EMG signal identification using MLP, RBF and LVQ methods in case of relevant features

A. Zeghbib[1], F. Palis[1], T. Schauer[2], R. C. Salbert[2],
[1]Otto-Von-Guericke Universität, Magdeburg, Deutschland
[2]Max-Plank-Institut für Dynamik Komplexer Technischer Systeme, Magdeburg

INTRODUCTION

Surface EMG signal-based hand movement identification for the control of prostheses is investigated. EMG surface electrodes are placed on two muscle groups: palmaris longus and extensor digitorum. From the input feature space, the classifier must be able to classify four hand movements: flexion of the thumb, the pointer and the middle finger movement as well as hand closing (HC). 34 single contraction periods are separated from the corresponding sets of continuous movementseach class has 17 training and 17 test patterns. The four classes have 68 train samples and 68 test samples. The initial transient part (400 ms) of each single contraction period is extracted from the raw signal and analysed with Short Time Fourier Transformation (STFT), an analysis method which gives a measure of both time and frequency information. Three relevant features, moment of second order (M2), central frequency (Fcnt) and standard deviation (Fstd), are extracted from surface EMG signals using time-frequency analysis methods for each channel. To distinguish the four different types of hand movements, we use three intelligent computational methods, Radial Basis Function (RBF) networks, Multi-Layer Perceptrons (MLP) and Learning Vector Quantization (LVQ) networks. In a first step the classification is applied on each feature separately using the above cited three methods. In the second step all three features are used together for classification applying each method. Finally, the Principal Component Analysis (PCA) algorithm is applied to reduce the dimension of our feature input space to two dimensions. PCA is used to reduce the dimensionality of a data set and to retain as much information as possible of the relevant information in the original multi-dimensional input feature space. In case of a big variation of variables in the multi-dimensional input feature space, the application of this algorithm will produce a loss of information which leads to a decrease in classification accuracy. All results are compared to resume the effect of the PCA dimension reduction algorithm on surface EMG signal classification with relevant features.

METHODS

PCA: We apply popular method of dimensionality reduction, which is the Principal Component Analysis. PCA is an eigenvector method designed to model linear variability in high dimensional data and computes the linear projections of greatest variance, i.e. get a maximum value of the quantity ($\mathrm{sum}(X_i - X\_mean)^2$) from the eigenvectors of the data covariance matrix. This reduction is achieved by taking m vectors X_1, $X_2, \ldots, X_m$ and finding the combinations of these vectors to produce principal components PC_1, $PC_2, \ldots, PC_p$, $p<m$, which are un-correlated. Principle Components are ordered so that PC_1 exhibits the greatest amount of the variation, then PC_2 exhibits the second greatest amount of the variation, and so on.

A -CLASSIFICATION OF EACH FEATURE USING LVQ, MLP AND RBF

1- Learning Vector Quantisation:

LVQ network used in this work has been tested for several neuron numbers composed the first competitive layer. In this type of network, LVQ, there is only one neuron affected in the second linear layer for each class. In this case, for several numbers of neurons, an optimal model is found during 25 train epochs. We train again our found optimal LVQ network during 100 iterations.

2- Multi-Layer Perceptron:

For the one-neuron output-layer we use log sigmoid transfer function “logsig”, which gives an output in the range of 0 to 1. Our output range between 0 and 1 will be divided in four ranges, since we have four classes to be identified.
MLP network used in this work has been tested first for several numbers of neurons in the hidden layer an during 25 epochs to get an optimal model. This optimal model will be trained again during 100 epochs.

3- Radial Basis Function Network:

We use the method, which creates neurons one at a time; the next neuron is added if the error is not low enough. This procedure is repeated until the error goal is met, or the maximum number of neurons is reached. The output layer is linear and the rate of classification is determined by the spread of the hidden unit. We give many values between 0.1 and 1 to find the optimal spread value.

4- Comparison of LVQ, MLP and RBF

We resume the comparison results about accuracy classification and misclassified instances of the three features M2, Fcnt and Fstd for all three classification methods LVQ, MLP and RBF in the following figure:

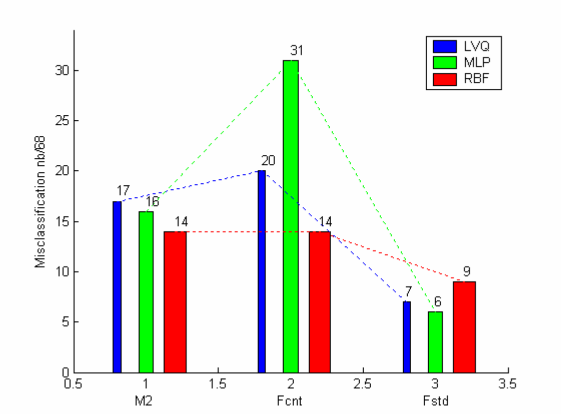

Figure 1: Number of total misclassified instances for three features out of 68 instances: M2, Fcnt and Fstd using LVQ, MLP and RBF classification methods.

B- CLASSIFICATION OF M2, Fcnt AND Fstd IN 6D-SPACE:

In the first part A of our study, the classification is applied on each feature separately using the three methods LVQ, MLP and RBF. In this second part, four movements will be classified using all these three features together in one input space. For each feature we have used two EMG channels that means our input space is composed of six features, figure 2a and 2b.

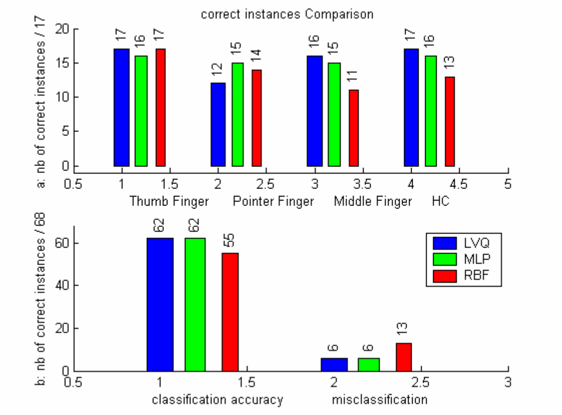

Figure 2a: Comparison of correct classified instances number for each movement corresponding to six features using LVQ, MLP and RBF methods

Figure 2b: Comparison of total correct- and misclassified instances number corresponding to six features: using LVQ, MLP and RBF classification methods.

C- CLASSIFICATION OF M2, Fcnt AND Fstd IN REDUCED 2D-SPACE:

In this third part of study, the input space dimension of the original data feature, which is equal to six, is reduced to two dimensional input spaces. This procedure allows us to present graphically our feature variables. The classification results are presented in figure 3a and 3b.

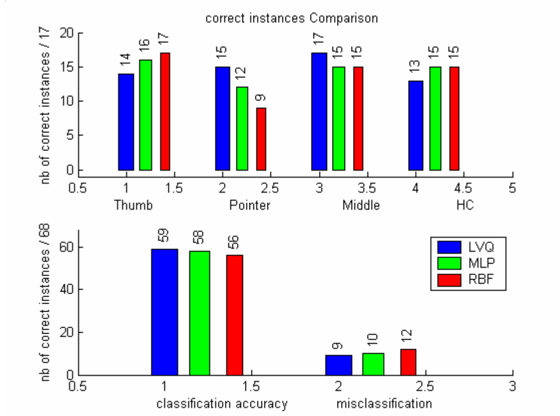

Figure 3a: Comparison of correct classified instances number for each movement corresponding to 2D reduced feature space with PCA for each movement using LVQ, MLP and RBF methods

Figure 3b: Comparison of total correct- and misclassified instances number corresponding to 2D reduced feature space with PCA: using LVQ, MLP and RBF classification methods.

CONCLUSION

Generally PCA transformation leads to a more discriminated representation of data. For relevant features, this procedure may decreases classification accuracy. The use of many features, in classification problems, doesn't lead necessarily to better results. In this study the feature Fstd in 2D-space gives by it self a less average number of misclassified instances with these used three methods, which is equal to 7,33 than in the case of 2D reduced space, which gives an average number of misclassified instances equal to 10,33. We can conclude that in classification problems it is more important to get a low dimensional space with relevant features.

REFERENCES

[1] [Haykin 1998]
S. Haykin, Neural Networks: A Comprehensive Foundation, (2nd Edition 1998), ISBN: 0132733501. Prentice Hall, 1998.

[2] [Jolliffe 2003]
I. T. Jolliffe, Principl Component Analysis", (2nd Edition 2003), ISBN: 0-387-95442-2. Springer.

[3] [Zeghbib 2005]
A. Zeghbib, F. Palis, G: Tsenov, V. Mladenov, N. Shoylev. *"Performance of Surface EMG signals Identification Using Intelligent Computational Methods". WSEAS TRANSACTIONS on SYSTEMS. Issue 7, Volume 4, July 2005. ISSN 1109-2777. http://www.wseas.org*