DIMENSIONALITY REDUCTION METHODS FOR CLASSIFICATION OF ACOUSTIC EMISSION SOURCES

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Abstract: This work examines the applicability of nonlinear matrix dimensionality reduction methods for separation of acoustic emission source types. The impact of normalization methods and feature domain selection on the separation quality is investigated.

Keywords: acoustic emission, dimensionality reduction methods, normalization, signal features

1 INTRODUCTION

Acoustic Emission (AE) is a natural effect whereby elastic waves suddenly appears in a material under mechanical stress. The elastic waves arise from the energy released during displacement in the structure of the material. Acoustic emissions in materials might be generated by several different physical processes. Distinction of these processes can be supported by analysis of the recorded signals. An AE signal itself is not directly related to its origin. Signals are affected by many factors such as the tested specimen, waveguide transfer function given by structure and homogeneity of material, transfer function of used sensors, etc. It contains a large amount of information, thus, it is more difficult to extract the information. Characteristic informations, namely features, can be extracted from acquired signals. These features are used to analyze the AE source, i.e. features form input data of cluster analysis for which the choice of dimensionality reduction method is crucial.

This paper analyses the usage of four selected dimensionality reduction methods to classify different AE sources. Analyzed signals were generated by two artificial sources for the purpose of objectivity.

2 OVERVIEW OF USED METHODS

The selection of the reduction method has a substantial effect on the result of analysis. A perfect reduction method would fully extract the varying information and reject all the redundancies.

2.1 REDUCTION METHODS

Principal Component Analysis (PCA) is a widely known and relatively simple analysis method. It can be easily used for dimensionality reduction. PCA is a linear transformation which places data points into a new space of principal components. The number of these components is the same as of original variables. They can be understood as vectors in the original space. The vector of first component has always the direction of maximal variability, therefor it is a maximization problem. The next vectors are orthogonal to all previous ones and the variability along them is gradually maximized. Since this is a linear orthogonal transformation, the distances and angles between input elements are preserved. The components are in the order of descending variability, hence a number of them can be omitted without loss of much information. In this way PCA can be used as a dimensionality reduction method [1].

Locally Linear Embedding (LLE) is a nonlinear dimensionality reduction based on pairwise distances of neighbors. It is intent on preserving the local structure of data points limited to a small number of surrounding points. LLE tries to create a low-dimension structure that retains the local layout observed in the original space. This is done, firstly, by finding k neighbors for each data points. Subsequently, the optimal weight matrix W is created by minimizing the cost function. This function calculates the reconstruction error in the original space. W contains coefficients for each point, which describe the influence of its neighbors to its own reconstruction. Ultimately, the cost function is minimized again for new low-dimensional data and the constant optimal W. In this way the distance error between nearby points is minimized and their local structure is reconstructed. This method does not consider all possible distances between the points, hence it does not try to retain the global structure or shape of original data [2].

Stochastic Neighbor Embedding (SNE) takes a probabilistic approach. The likeliness of that two points are neighbors is based on Gaussian distribution. It depends exponentially on the ratio of dissimilarity between the two points and the sum of all other dissimilarities [3]. SNE has a disadvantage considering cluster analysis. The "attractive" forces among all points dominate over "repulsive", consequently, clusters existing in the original space have a tendency to move toward each other, this phenomena is also referred as the "crowding problem". This problem is solved by the method t-SNE which replaces the Gaussian by Student's distribution. It has stronger side lobes, which reduces the "attractive" forces and, additionally, is computationally simpler. Using t-distribution data points are "repelled" more, allowing gaps to arise between clusters of points [4].

The method Laplacian Eigenmaps (LEM) is based on the graph theory. It approximates the high-dimension data by graph, where data points near to each other are connected by an edge. The criterion of connecting is either based on the distance or the n nearest neighbors are connected. After that, a weight is assigned to every graph edge. This can be a heat kernel (depending on the exponential of distance) or simple-minded (1 for every existing edge). A weight matrix is created representing the graph edges by weights. Subsequently a general eigenvector problem is formulated using the weight matrix. The resulting eigenvectors are used for embedding points in the low-dimensional space [5].

2.2 NORMALIZATION METHODS

Signal features have various units and magnitudes. The absolute scale of a specific feature can highly affect the result of dimensionality reduction while it contains no information, therefor, the normalization plays a key role in the process of analysis. Normalization changes the scale of data to fit the range $\langle 0, 1 \rangle$.

In this research, the following normalization techniques were used. Normalization of range of values (range) is a linear transformation. It transforms the values that the lowest will be transformed to 0 and the highest to 1. Variance normalization (var) is also a linear transformation that aims the output data to have variance of 1. Logistic normalization normalizes the data using the logistic curve. Firstly data are normalized to have unity variance, after that, the logistic function is applied. This transformation is close to linear in the middle range. However, it compresses the outlying data points, thus, all remain in the specified range. Discrete histogram normalization (histD) is a nonlinear technique. The input values are ordered and, subsequently, the numbers are replaced by their ordinal number. Continuous histogram normalization (histC) is a partially linear transformation. The value range is divided equally into bands. The number of bands is the square root of unique input values. The values within a band are transformed linearly between $\langle n, n+1 \rangle$, where n is the ordinal number of band. After all, the result is range normalized to $\langle 0, 1 \rangle$ [7].

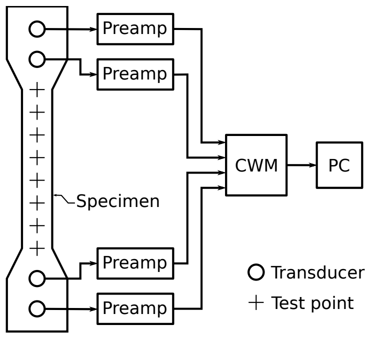

Figure 1: Experimental setup

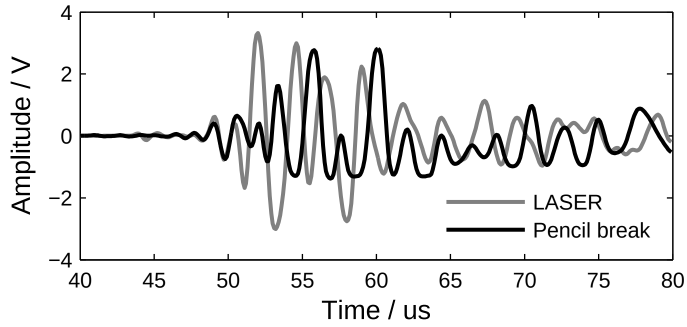

Figure 2: AE signals generated by LASER pulse and pencil break at the same test point

3 RESULTS AND DISCUSSION

In this research, AE signals were generated by short high-energy LASER pulses and by pencil break. These signals are shown on Fig. 2. AE signals generated on the specimen were recorded using 4 piezoelectric resonant sensors and acquired by a record system (CWM - Continuous Wave Memory) [6].

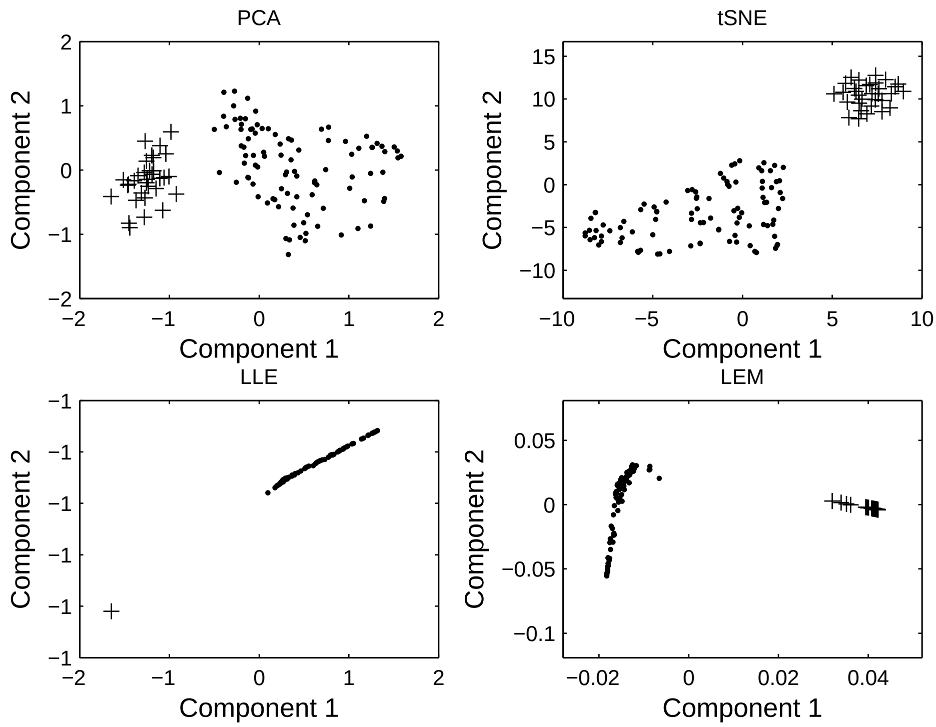

Figure 3: Results of reduction methods for 2 components: PCA, tSNE, LLE, LEM. Dots and crosses represent signals generated by pencil breaks and LASER pulses, respectively.

The assessment of the result of reduction methods is done using the separation ratio between the two sets of points in the low-dimensional space. The separation ratio is defined as d_{min}/d_{max}, where d_{min} and d_{max} are the shortest and longest distance between a pair of data points, respectively, one from each set.

The two set of points form two separated clusters when the separation ratio is above 0.1. When it is higher than approx. 1.5, practically no data point is classified erroneously. This case is shown on Fig. 3. where the separation ratio of PCA is 1.6. Data points clearly form 2 clusters. The clusters are separated according to the source type. The results of reduction methods related to neighborhood (tSNE, LLE, LEM) are sensitive to the neighbor selection criterion. The optimal number of neighbors was selected between 6 and 10 for particular reduction method (tSNE, LLE, LEM). This value can be slightly varied without significant drop of separation ratio.

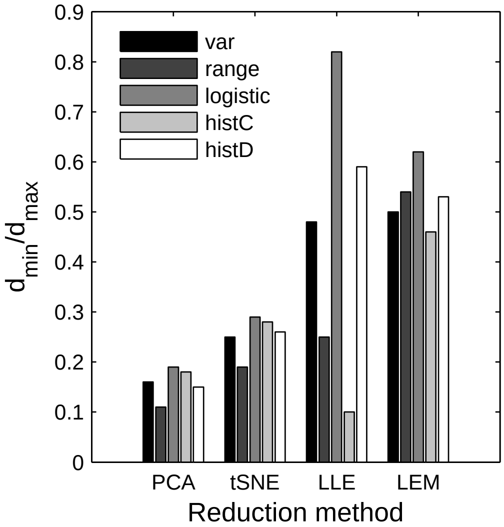

Figure 4: Comparison of separation ratio of normalization techniques

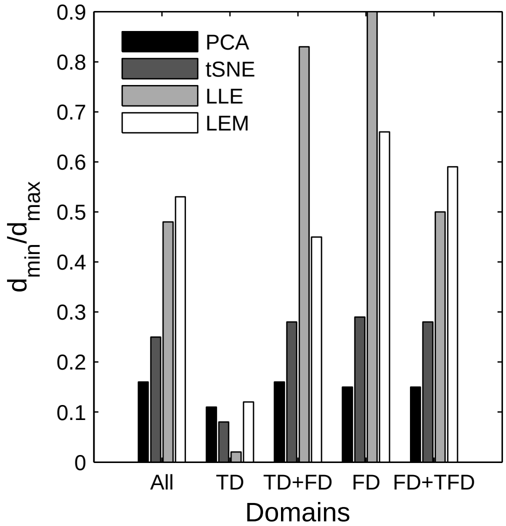

Figure 5: Comparison of separation ratio of feature domain sets

3.1 Influence of Normalization of Input Data

The influence of normalization techniques on the separation is shown in Fig. 4. Omitting the normalization step, d_{min}/d_{max} is in all cases far below 0.1. It was not worthy to include it on the graph. Range normalization is a basic method and in most of cases the achieved separation ratio is lower than with other methods.

Figure 4 shows that the performance of neighborhood-based techniques exceed PCA. It is a rather simple method, it gives fairly good results, however. The logistic normalization is clearly outstanding. This method reduces the influence of data which lie relatively far from others. Such data are often caused by measurement errors. Although they have low significance, they could be treated by the reduction method important due to its perturbed distance. Histogram normalization can also partially eliminate exserted data. HistC has good performance with PCA and tSNE, whereas histD achieves better results with methods strictly based on connecting neighbors (LLE, LEM).

3.2 Influence of Choice of Signal Features

Each feature represent a property of signal that is calculated by a unique algorithm. Time domain (TD) features are evaluated from the signal shape in time. Such features are the maximal amplitude of the signal, duration, envelope rise time, period count, period count to peak, amplitude of the first cycle and statistical moments, etc. Frequency domain (FD) features are calculated from the Fourier transformation of each signal. Most basic features are the maximal amplitude and its corresponding frequency. In addition, the spectrum is divided into 6 bands and the energy of each band is computed. Time-frequency domain (TFD) features rely on the wavelet transformation of the signal. The features investigated herein are the frequency of the first peak and the frequency of the highest peak. TFD features are in a highly experimental phase, and they are not widely used.

Figure 5 manifests the impact of choosing feature categories and their combinations on the quality of separation, further, this figure shows that time domain features themselves have low performance in this case. If other features are combined with TD, the quality of separation slightly drops. Best results are achieved using frequency domain features exclusively.

It can be seen, that the quality order of features domain combinations can not be unequivocally established. While the results of tSNE are moderate in all combinations except TD, LLE and LEM shows excellent but varying performance depending on the used domain combination. This could be caused by relatively high difference of signals in the test set.

4 CONCLUSIONS

In this work, the dependence of separation quality on selected modern normalization methods and feature domain selection were evaluated. It has been shown that modern nonlinear dimensionality reduction methods are exceedingly suitable for characterization of acoustic emission sources.

On the basis of results it can be concluded, that FD features carries most of information, while combination with other features decreases the separation ratio. This may not be true globally. In other specific situations other domains may carry more useful information, hence, their usage cannot be totally deprecated. The FD features mostly consist of energies in defined frequency bands, while their change in time is not considered. The time variation is likely to carry useful information. This type of feature falls among TFD. It would determine the energy in frequency bands sectioned in time. Considering these time changes should have positive impact on the result of separation for all reduction methods.

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