Smart Feature Extraction from Acoustic Camera Multi-Sensor Measurements (Extended Abstract)

Volodimir Kudriashov[1], Kiril Alexiev[1], Petia Koprinkova-Hristova[1], ???[2]

[1]IICT, Bulgarian Academy of Sciences, Acad. G. Bonchev str. bl.25A, Sofia 1113, Bulgaria
[2]TU-Sofia

Abstract. The paper applies recently developed smart approach for feature extraction to the task for classification of focalized spectra obtained from multi-sensor measurements using acoustic camera. The aim of the study is development of distance diagnostic system for prediction of wearing out of bearings using real time noise measurements.

Keywords: smart signal processing, multi-sensor system, feature extraction, classification, Echo state network, IP tuning

1 Introduction

Localization of sound sources is a task with numerous practical applications. Variety of special purpose devices were created for this aim. Among these acoustic cameras consisting of multiple microphones are the most sophisticated multi-sensor systems that allow precise location and differentiation of different noise sources. In present study the Brüel & Kjær system was used.

The main aim of our work was to collect data base of noise measurements from undamaged and worn out bearings in real working conditions and to create a distance diagnostic system allowing prediction of bearings failure without machine disassembling. Extraction of descriptive characteristics needed for classification from the accumulated multi-dimensional sensor data needs deep expert knowledge and usually results in huge number of obtained features. In present study we apply a recently developed smart approach using Echo state networks (ESN) for feature extraction and reduction that results in increased classification accuracy of the trained diagnostic system.

2 ESN for feature extraction and reduction

The feature extraction and reduction approach was developed in our recent works [1-3]. Fig. 1 describes briefly in program-like code the basics of our algorithm.

adfa, p. 1, 2011.

```
in(1:data dimension,1:data size);
n_in=data dimension; n_out=1; n_r=chosen number;
nclass=chosen number;
esn=generate_esn(n_in, n_out, n_r);
for it=1:number of IP iterations
        for i=1:data size
                esn=esn_IP_training(esn, in(:,i));
        end
end
for i=1:data size
        r(0)=0;
        for k=1:chosen number of steps
                r(k)=sim_esn(esn, in(:,i),r(k-1));
        end
        r_e(i)=r(k);
end
p=0;
for i=1: n_r-1
        for j=i+1: n_r
                p=p+1;
                projection(p)=create_projection( r_e(i), r_e(j));
        end
end
for i=1:p
   clussifier(p)=train_classifier(projection(p), nclass);
end
select projection(s) resulting in the best classifier;
```

Fig. 1. Algorithm for multidimensional data clustering.

Here ESN is a special kind of recurrent neural network [4] consisting of randomly generated dynamic reservoir. The core of our approach consists of fitting the reservoir connections to the data structure using IP training algorithm [5] and next exploriting of the reservoirs neurons equilibrium states as a pool of features. It was shown [1] that generation of variety of 2D projections (using all possible combinations of two features) allows us to "see" the multidimensional data set from different viewpoints and thus to find a view that discovers in the clearly its structure. The features in chosen 2D projection are further used to train a classifier of the original multi-dimensional data set.

3 Acoustic camera and bearings measurement results

Noise generated by healthy and worn out bearings was measured during their work on a laboratory test-bed using Brüel & Kjær acoustic camera.

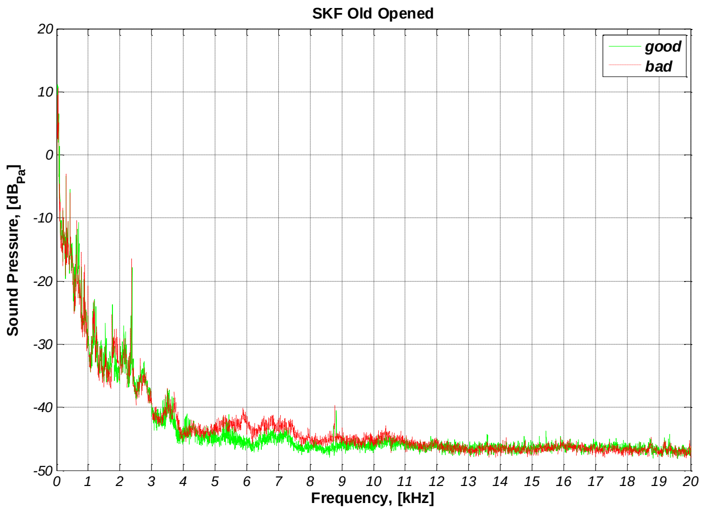

Fig. 2. Focalized spectra of healthy (good) and damaged (bad) bearing.

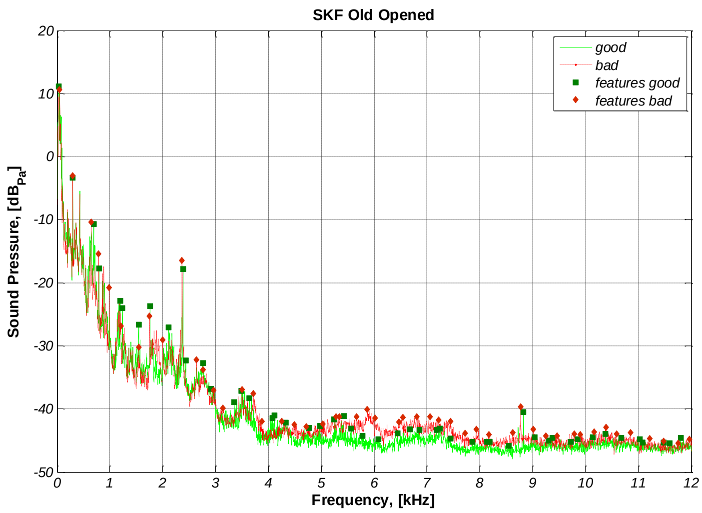

Fig. 3. Original data set features denoted by squares and rhombs for the good and bad bearing respectively.

Then the multi-sensor data was "fused" to produce a focalized spectra characterizing noise at the position of interest (the tested bearing). The comparison between healthy ("good") and damaged ("bad") SKF bearing was shown on Fig. 2. From it we conclude that two spectra differ mainly for the frequencies bellow 12 kHz. Since the characteristics extracted from this kind of spectra are peaks of sound pressure and corresponding to them frequencies, we decided to divide the range between 0 and 12 kHz into 50 intervals and to find local maxima in all of them. Thus the original data set features consists of 50 pairs of local maxima and corresponding to them frequencies, i.e. we have total 100 features shown as squares and rhombs on Fig. 3.

4 Results and discussion

The defined in such way 100 features obtained from measurements of variety of undamaged bearings and bearings with different kind of damages will from the multi-dimensional data set *in*(1:100,1:number of test bearings) fed to the ESN for features extraction. We will then use the extracted features to train k-means, fuzzy C-means and other classifiers to separate the bearings into two classes ("healthy" and "worn out") according to measured by the acoustic camera focalized spectra.

5 Conclusions

The proposed approach for feature extraction and classification will lead to development of distance diagnostic system with acoustic camera that will allow diagnosing bearings without disassembling or approaching of the machines in real working conditions.

Acknowledgments. This work was partly supported by the project AComIn, grant 316087, funded by the FP7 Capacity Program (Research Potential of Convergence Regions).

References

1. Koprinkova-Hristova, P. and N. Tontchev, Echo state networks for multi-dimensional data clustering", Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 7552 (PART 1), pp.571-578, 2012.
2. Koprinkova-Hristova, P., Alexiev, K., Sound fields clusterization via neural networks, 2014 IEEE International Symposium on Innovations in Intelligent Systems and Applications, INISTA 2014; June 23- 25, 2014, Alberobello, Italy, pp.368-374.
3. Koprinkova-Hristova, P., Alexiev, K., Dynamic sound fields clusterization using neuro-fuzzy approach, 16th International Conference, AIMSA 2014, Varna, Bulgaria, September 11-13, 2014, Artificial Intelligence: Methodology, Systems, and Applications, Lecture Notes in Computer Science, vol.8722, 2014, pp.194-205.
4. Lukosevicius, M., Jaeger, H.: Reservoir computing approaches to recurrent neural network training. Computer Science Review. 3, pp. 127--149 (2009)
5. Schrauwen, B., Wandermann, M., Verstraeten, D., Steil, J.J., Stroobandt, D.: Improving reservoirs using intrinsic plasticity. Neurocomputing. 71, pp. 1159--1171 (2008)