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Effects of Sound Radiation Direction In Faulty Hermetic Compressors

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ABSTRACT

The Neural Networks and especially Self Organizing Map are used in general for the classification problems. The same technique is used in this paper to classify the possible failures, which can be encountered in Hermetic Compressors, during the R/D phase or after the production line. Here, those failures are created deliberately in different compressors, and the sound pressure data has been collected with 10 different microphones. In order to discriminate the faults, SOM and LVQ techniques are used. However the main aim of this paper is to scrutinize the effects of the microphones' directions and locations while recording the both healthy and the faulty compressors' sounds. For each microphone, its total corresponding effect has been calculated using Principal Component Analysis (PCA) method and it has been found that, some microphones have superior contribution on the recognition of the faults, but the others have minimal effect. This demonstrates that while getting the sound pressure data, its location has great importance to achieve a successful classification.

1. INTRODUCTION

The hermetic compressors which are commonly used in household refrigeration systems are the most important noise and vibration sources. There are abounding researches carried on compressors in order to reduce the noise emanated from those devices. The failures which increase the noise level in the compressors may be a consequence of a malfunctioning in the production line or may be inherited from the R/D phase. Since there are different reasons for different types of noises, so not only the overall level but also the type of emitted noise from the devices have great importance in order to identify the possible failures for the compressor.

In the plants, although there are plenty different precautions taken into consideration to catch faulty compressor in the production line, the main aim is nailing the faulty compressors in the line. However, from the point of view of robustness of the production process, it is necessary to focus on to the techniques to scrutinize the deficiencies causing the related fault. On the other hand, because of the mechanical structure, the sources of these faults cannot be resolved unless the compressor is disassembled. Since it is not possible to reuse the compressor that is disassembled due to some unknown fault in serial production, detecting the source of the problem may prevent loss of time and the investment. The goal of the present study is to identify the common faults by means of acoustical measurements without disassembling the compressors and scrutinizing the relative effects of the localizations of microphones on the results of the classification process. Here it is also possible to carry on same kind of techniques for the prototypes of new designs, in order to save time and shaping the designs.

In literature, there are plenty many researches are carried on fault analyzing using neural networks. (Germen, *et. al.* 2005) It is strictly proposed to the reader to check the paper (Kaya, *et. Al.* 2008) in order to apprehend the possible usage of SOM to discriminate 5 different failures which are in common in hermetic compressors. Using neural

network tools, it is aimed to recognize common faults by investigating the compressors in a controlled manner. In order to gather the data to be used in neural network analysis, some common serious faults have been implemented one by one on the compressors which are chosen such that they do not have any of these faults at the beginning. After performing a series of detailed acoustic and vibration tests on these base compressors, controlled faults related to muffler, shock loop tube, motor, case and springs are implemented on them one by one. At each time the fault is implemented, the series of tests are conducted and these tests are repeated at each step. 17 compressors were selected for the tests. All the experiments were done with these compressors. Six series of experiments (one with the normal and one with each of the five faulty conditions) for each of the 17 compressors, that are 102 experiments in total, were designed and conducted.

All of the measurements are carried out in a semi-anechoic chamber up to ISO 3745. The sound power level of each of these compressors is measured by 10 microphones as described in ISO 3745 standard after the compressors reach steady state conditions. 1/3 octave sound spectra for all of these 10 microphones is measured. There exist two different approaches to analyze the data. First one uses a weighted average of all 10 microphones' measurements. Second approach uses all data from each microphone separately, which means larger input files and higher computation time, when compared to the first approach but has the ability to investigate the fault regions in a more detailed way. In this study, since the faults could not reach high separation ratios using the first method, the second method is used. According to the results, each fault can satisfactorily be identified using the second approach when sufficient training is done.

In this paper it is mainly concentrated on the effects of the localizations of the microphones in the semi-anechoic chamber since there is a one to one relationship with the direction of radiation of a sound field and microphone positioning. Although ten microphones are used in a hemispherical arrangement in order to get acoustic data, it is searched that whether all the ten microphones have the same kind of contribution to the discrimination of the faults or not. If not, it could be possible to lessen the amount of microphones. Decreasing the size of the microphones immediately effects the computation times and has directly impact on fault recognition phase. Using the results obtained from the experiments it is possible to increase the quality of classification problem.

In section 2, a very brief introduction of SOM (Self Organizing Map) has been introduced which is used to find the possible clusters for different data sets. Also the proposed map dimensions and the characteristics of the feature vectors in order to train the map will be introduced in this section. In section 3 the PCA technique is delineated and the method to investigate the effects of microphones is described in this chapter. The results obtained from experiments will be discussed in section 4 which concludes the paper.

2. SOM (SELF ORGANIZING MAP) AND LVQ (LEARNING VECTOR QUANTIZER)

Kohonen's SOM (Self Organizing Map) is an impressive tool to visualize the possible classes occurring in high dimensional data sets. The theory of SOM has inspired from the structural organization of neurons in cerebral cortex in human neural system. (Kohonen, 1995) It is observed that some specific areas of brain tissue are organized according to the types of the input signals in adaptive and automatic nature. Similarly, SOM shows same kind of organization in unsupervised manner. SOM in general provides a projection of high dimensional data set which has a character $\Gamma = \mathfrak{R}^n$ into m many codebook vectors of size n to two dimensional domains. It is also worth to mention that, the organization of codebook vectors with connection in two dimensional planar surfaces, keeps the relational information between the input data which provides us clustering information.

In SOM, the learning period is described as :

$$M_i(k) = M_i(k-1) + \alpha(k) \cdot \beta(i, c, k) (\Gamma(k) - M_i(k-1)) \quad (1)$$

where $\alpha(k)$ is the learning rate parameter which is changed during the adaptation phase and $\beta(i, c, k)$ is the neighborhood function around c where c is the Best Matching Unit (BMU) index which can be found during training as:

$$c = \arg \min_i \|\Gamma(k) - M_i(k)\| \quad (2)$$

The interpretation of above equation requires explanation of parametric learning rate and neighboring function. Learning rate has decreasing characteristic during the learning period which effects the changing positions of the neurons in lattice. For the most of the applications, the general approach is fast at the beginning and slow at the end of the learning phase. The neighborhood function describes the impact area around BMU which describes how the neighboring neurons will be drawn near to BMU. The BMU describes the winning neuron in the training phase where index c is determined by equation 2.

In this work the feature vectors $\Gamma = \mathfrak{R}^n$ where $n = 25$ are used to train the 5x10 SOM neurons which has connected in Hex-lattice manner. The 25 components of feature vectors are obtained from only one microphone which is investigated for the effect on discrimination of failures.

After obtaining the possible codebook vectors using SOM training algorithm which is an unsupervised technique, the possible classification regions should have to be obtained in supervised manner. In literature Learning Vector Quantization 3 (LVQ3) algorithm (Kohonen, 1990) is the one of the most suitable technique in order to delineate and adjust the crossing borders of the possible classification regions.

The LVQ-3 algorithm can be explained as:

$$\begin{aligned} M_i(k+1) &= M_i(k) - \mu(k)(\Gamma(k) - M_i(k)) \\ M_j(k+1) &= M_j(k) + \mu(k)(\Gamma(k) - M_j(k)) \end{aligned} \quad (3)$$

Where M_i and M_j are the two closest codebook vectors to $\Gamma(k)$, whereby $\Gamma(k)$ and M_j belongs to the same class, while $\Gamma(k)$ and M_i belong to different classes respectively; furthermore $\Gamma(k)$ must fall zone of a *window* defined as;

$$\min\left(\frac{d_1}{d_2}, \frac{d_2}{d_1}\right) > s \quad \text{where } s = \frac{1\text{-window}}{1+\text{window}} \quad (4)$$

where d_1 and d_2 are the distance between codebook vectors $M_i - \Gamma(k)$, and $M_j - \Gamma(k)$. Also it is necessary to have:

$$\begin{aligned} M_i(k+1) &= M_i(k) + \varepsilon(k)\mu(k)(\Gamma(k) - M_i(k)) \\ M_j(k+1) &= M_j(k) + \varepsilon(k)\mu(k)(\Gamma(k) - M_j(k)) \end{aligned} \quad (5)$$

where M_i and M_j are the two closest codebook vectors to $\Gamma(k)$, whereby $\Gamma(k)$ and M_j and M_i belong to same classes. The $\varepsilon(k)$ and $\mu(k)$ parameters are learning rates in the algorithm.

3. IMPACT FACTOR ANALYSES OF ACOUSTIC DIRECTION OF COMPRESSOR SOUND

PCA is one of the most apprehended tools derived from the linear algebra. It is used in different areas where data reduction is the main objective. From neuroscience to computer graphics, from digital signal processing to econometrics, when it is necessary to extract the relevant information from the complicated and extensive data set, PCA provides a roadmap with minimal effort.

In PCA, the aim is finding another basis which will be a linear combination of the original basis which expresses the data set best. It can be achieved by optimal linear transformation of data matrix X in terms of variations in data as:

$$T = XP \quad \text{and} \quad X = TP^T \quad (6)$$

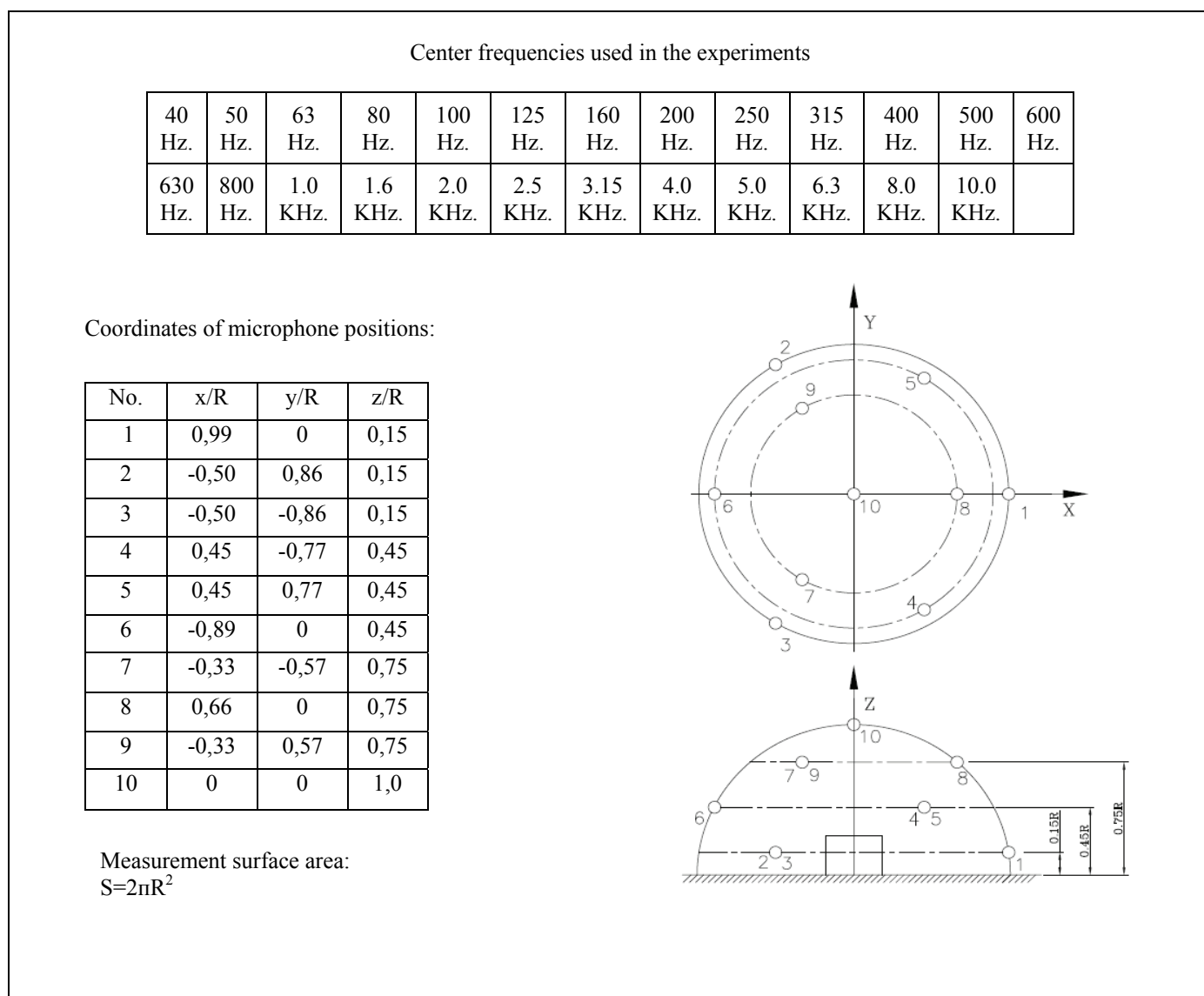
Where $T \in \mathbb{R}^{N \times n}$ which is the principal component matrix, and the $P \in \mathbb{R}^{n \times n}$ contains the principle vectors which are the eigenvectors associated with the eigenvalues λ_i of the covariance matrix Y of X such that:

$$Y = P\Lambda P^T \quad \text{with} \quad PP^T = P^T P = I_n \quad (7)$$

Where $\Lambda = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_n)$ a diagonal matrix with diagonal elements are ordered in decreasing manner.

In this work PCA technique is used in order to discriminate the most effective microphones from the 10 microphones set. In order to accomplish this task, the data which are taken from 10 different microphones for 102 experiments is used. Each microphone's time domain data is converted to frequency domain and 25 point data which spans 40 Hz- 10KHz. region are obtained. Except the healthy compressor, five different faults have been generated. Those faults are about springs, casing, shock loop tube, suction muffler and motor. In the figure given below the center frequencies and the positioning of the microphones are given.

Figure 1. Microphone positioning and center frequencies



In order to delineate the effect of the contribution of each microphone, first 10 microphones are used to produce 25 eigenvectors corresponding 25 different frequencies. After those eigenvectors are recorded, the same calculations have been carried on by taking one microphone out. For each calculation, again the 25 eigenvectors are calculated and distance comparisons done with the result obtained with 10 microphones set. An example for first three experiments are tabulated as:

Table 2 : Differences between eigenvectors obtained using 10 microphone and 9 microphone set

	<i>Mic 1</i>	<i>Mic 2</i>	<i>Mic 3</i>	<i>Mic 4</i>	<i>Mic 5</i>	<i>Mic 6</i>	<i>Mic 7</i>	<i>Mic 8</i>	<i>Mic 9</i>	<i>Mic 10</i>
Exp 1	29.375	28.2888	29.5735	30.0969	29.7887	32.089	28.2962	25.9964	27.9802	32.1557
Exp 2	29.453	26.5609	29.148	29.6114	29.0773	34.2517	29.3657	27.4356	28.0148	33.8473
Exp 3	30.6207	30.1759	30.1886	30.4633	30.5261	32.1384	27.2973	26.3097	28.3263	29.6506

Here the rows denote the experiment (Exp1 = Healthy motor of serial number 895, Exp 2 = Spring error with serial number 895, and Exp3 = Casing error of serial number 895, etc.) and the columns denote the Euclidian distance in eigenvectors obtained using ten microphone set and 9 microphone set (Col 1 represent eigenvector distances obtained by taking microphone 1 out, column 2 represents eigenvector distances calculated taking out of microphone etc.) The greater value in a field represents the greater impact factor of related microphone. For example if microphone 10 is taken out in Exp 1, it is found that the distance between the eigenvectors obtained with ten microphones set and 9 microphones set has the greatest impact however, in Experiment 2 when the microphone 6 is taken out, the most degradation in principal component vectors are obtained. In order to grasp the effect of the microphones, this eigenvector differences are converted into a rank table as:

Table 3 : Rank table

	<i>Mic 1</i>	<i>Mic 2</i>	<i>Mic 3</i>	<i>Mic 4</i>	<i>Mic 5</i>	<i>Mic 6</i>	<i>Mic 7</i>	<i>Mic 8</i>	<i>Mic 9</i>	<i>Mic 10</i>
Exp 1	4	3	6	8	7	9	4	1	2	10
Exp 2	6	1	5	8	4	10	6	2	3	9
Exp 3	8	5	6	7	8	10	2	1	3	4

Here in experiment 1 for example, the microphone 10 has the greatest impact factor however the microphone 8 has the minimal effect. After converting the differences of eigenvectors to their corresponding rank value, the impact factor which denotes the contribution of each microphone is calculated by adding its corresponding rank for 102 experiments. The results are given in table 3 and here it is seen that the Microphone 6 has a great influence in microphone data set however Microphone 7 has less effect.

Table 4 : Impact factors of each microphone

	<i>Mic 1</i>	<i>Mic 2</i>	<i>Mic 3</i>	<i>Mic 4</i>	<i>Mic 5</i>	<i>Mic 6</i>	<i>Mic 7</i>	<i>Mic 8</i>	<i>Mic 9</i>	<i>Mic 10</i>
Effect	952	853	1225	1093	1339	1489	768	1026	896	1213

In order to analyze the corresponding effects of each microphone on determination of classification regions, the SOM maps have been obtained. Although only the SOM Map for microphone 6 and SOM Map for microphone 7 are given in figure 3 and figure 4., the whole maps are obtained for all the experiments carried on taking of each microphone away. It has been observed that there is a one to one relationship between the impact factor of a microphone and the quality of classification of errors.

Figure 2. SOM Map obtained using Microphone 6

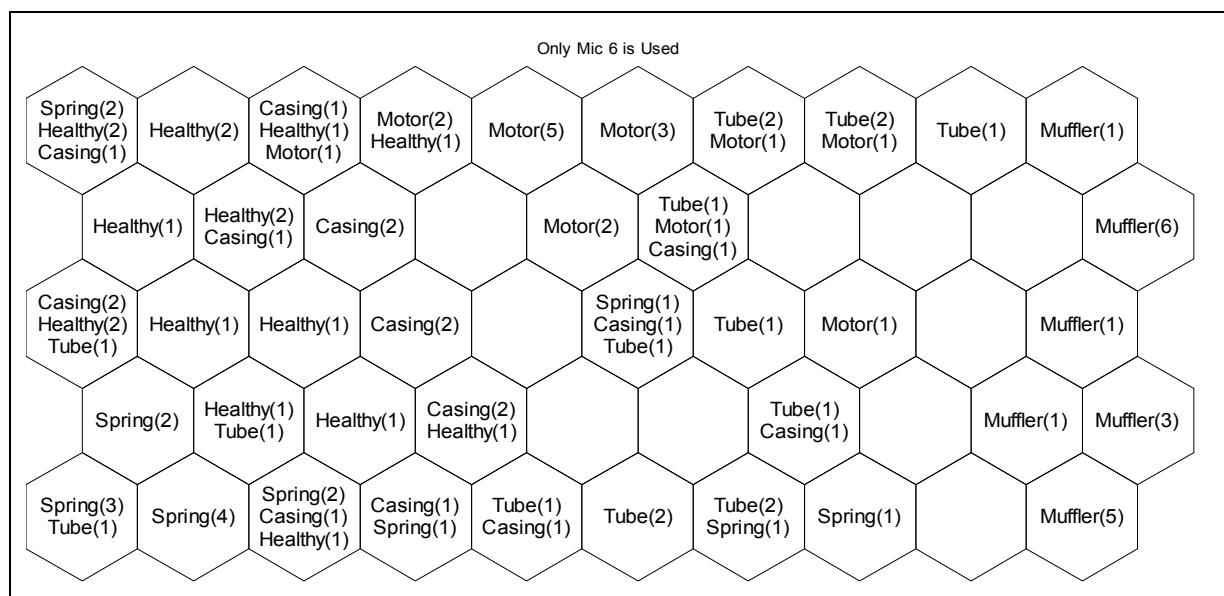
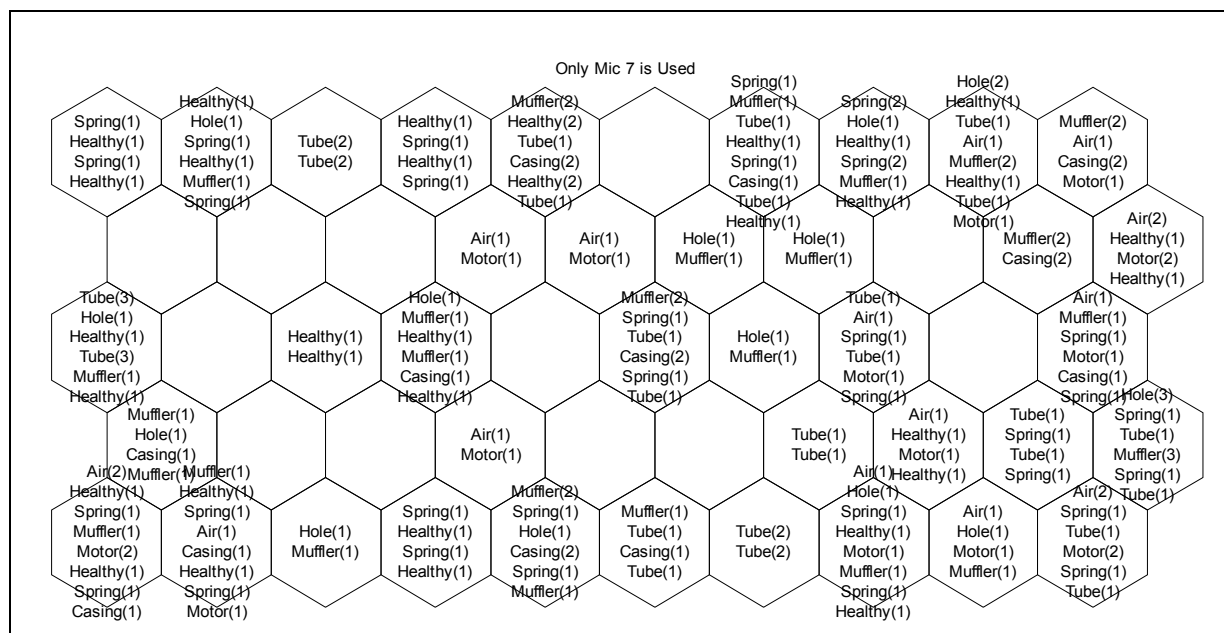


Figure 3. SOM Map obtained using Microphone 7



It is clearly seen from the figures that, the microphone 6 provides considerably valuable information for the clustering problem. The muffler error has been discriminated from the others and the healthy motors are grouped together which forms a classification region. It is also investigated that the casing fault has no significance, easy to mix with different kind of faults and difficult to classify. However by investigating of Figure 4, it is almost impossible to observe the possible classification borders. This microphone doesn't produce usable information for the classification problem.

4. RESULTS & CONCLUSIONS

The results obtained from the experiments and analysis tools described in this paper provide valuable information about the effect of noise radiation direction in classifying different types of common faults. It is observed that some microphones have much greater contribution in determination of the clustering regions. According to the results of analysis, 6th microphone has the greatest impact while 7th has the least. The data obtained from the 6th microphone clearly classifies muffler errors and healthy compressors. The knowledge of directivity of noise radiation can be used as a powerful tool for discriminating faulty compressors both during R/D phase and on the production line. Due to physical and timing limitations gathering the data from the right orientation is very critical for achieving the correct results. Therefore the outcomes of this study form a considerable basis for determination of microphone positions for successful clustering in fault analyses.

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