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Exploring Pattern Recognition For Bearing Fault Diagnosis

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ABSTRAK

Diagnostik sensorik bantalan tradisional termasuk sentuhan dan pendengaran bergantung pada pengalaman pribadi, dan untuk sistem yang lebih kompleks tidak dapat memenuhi kebutuhan diagnosis kesalahan peralatan. Penelitian tentang diagnosis kerusakan bearing berkembang secara signifikan. Bearing digunakan dalam mesin berputar dan sebagian besar kegagalan mesin disebabkan oleh kegagalan bearing. Diagnosis kesalahan bearing merupakan area penelitian yang penting. Inti dari diagnosis kesalahan bearing adalah pengenalan pola fitur kesalahan. Kunci pengenalan pola adalah mengembangkan pengklasifikasi yang masuk akal. Pengenalan pola cerdas telah dikembangkan seperti komponen utama, mesin pendukung vektor, jaringan saraf. Dalam studi ini, diagnosis kesalahan bearing berdasarkan eksplorasi pengenalan pola yang diusulkan. Kunci pengenalan pola adalah merancang pengklasifikasi yang signifikan. Sejumlah fitur dari getaran bearing normal dan bearing sesar diekstraksi dan diproses menggunakan komponen utama matriks korelasi. Plot komponen utama menunjukkan visualisasi bearing normal dan kesalahan dan pengklasifikasi dipilih secara subyektif. Eksplorasi komponen utama akan dikonfirmasi menggunakan mesin vektor dukungan kuadrat terkecil. Parameter support vector machine diestimasi menggunakan optimasi heuristik particle swarm optimization. Metode yang diusulkan dapat diterapkan dalam mendeteksi kesalahan bearing.

Kata kunci: diagnosis bearing, pengenalan pola, komponen utama, Hotelling T^2

ABSTRACT

Traditional bearing sensory diagnostic include touching and hearing rely on personal experience, and for more complex system are unable to meet the needs of equipment fault diagnosis. The research on bearing fault diagnosis is developing significantly. Bearings are used in rotating machinery and most machinery failures are caused by bearing failures. The fault diagnosis of bearings is an important research area. The core of bearing fault diagnosis is the pattern recognition of fault features. The key of pattern recognition is to develop a reasonable classifier. Intelligent pattern recognition has been developed such as principal components, support vector machine, neural network. In this study, a bearing fault diagnosis based on exploring pattern recognition is proposed. The key to pattern recognition is to design a significant classifier. A number of features from bearing vibration of normal and fault bearing are extracted and processed using principal components of correlation matrix. Plot of principal components shows the visualization of normal and fault bearing and the classifier is chosen subjectively.The principal components exploration will be confirmed using least squares support vector machine.The parameter of support vector machine estimated using heuristic optimization particle swarm optimization. The proposed method can be applied in the detection of faults of bearing.

Keywords: bearing diagnosis, pattern recognition, principal component, Hotelling T^2

1. INTRODUCTION

Bearing laboratory experiment collect a huge amount of data regarding vibration, temperature and so on, which are of particular interest for the bearing fault diagnosis. Bearing data sets present the following features: multivariate as several variables are simultaneously measured, measurements are taken under different bearing condition: normal or fault bearing. Multivariate techniques represent useful tool for analyzing multiple variables. The main goal is to obtain summary description of the data. Principal component analysis finds a smaller number of variates representing all those collected without losing essential information. Bearings are key components of rotary mechanical system. The failure of bearings can lead to downtime and economic losses. One-third of malfunctions of mechanical system are caused by bearing failure. Monitoring bearing condition, bearing diagnosis, is an important aspect on machinery maintenance. Once failures occurs it will cause a chain of destruction.

Bearing defects are commonly detected using vibration analysis as simple and nondestructive (Abidova, Lapkis, and Chernov 2019). A singular spectrum analysis was proposed as a method for bearing fault detection (Bugharbee and Trendafilova 2018). Principal components was proposed to identify the healthy and different faulty bearing (Elsamanty, S. Salman, and A. Ibrahim 2021). Multivariate statistical process was proposed as bearing fault detection framework (Jin, Fan, and Chow 2019). Vibration analysis has been used as a predictive maintenance procedure in bearing maintenance. By analyzing the bearing vibration it is possible to predict bearing failure (Kirankumar et al. 2018). A defect diagnosis technique based on empirical mode decomposition aims at extracting bearing defect characteristics (Li and Qi 2020). An adaptive signal decomposition based on singular spectrum analysis was developed and has been used in the bearing fault diagnosis (Pang, Tang, and Tian 2019). Principal components, discriminant analysis and support vector machine was proposed as fault detection method in a power distribution network (Sarwar et al. 2020). Kernel principal components with support vector machine was developed as a method to classify the defects of bearing used in induction motor (Prakash Yadav and Pahuja 2019). Principal components was proposed as an extraction index to analyze the states of bearing life cycle (Yuan and Chen 2020). A fault diagnosis method based on principal components and learning system was developed to increase the efficiency of fault identification (Zhao et al. 2019). The support vector machine was studied as an intelligent diagnosis method for intelligent fault diagnosis (Zhou et al. 2016). Principal component is a powerful bearing fault detection. However principal component based on covariance matrix is sensitive to outliers. A two step principal component was proposed to remove the effect of outliers on principal component model (Tharrault et al. 2008). An improved learning algorithm is proposed to reduce the cost of bearing fault diagnosis (Tharrault et al. 2008). A deep learning, convolutional neural network, has been proven to be a promising bearing fault diagnosis (Liu et al. 2021).

In this article, principal components and Hotelling T^2 are combined to detect a shift in bearing vibration. Twelve features are extracted from bearing vibration of normal bearing and failure bearing. Principal component analysis of correlation matrix of these data produces eigenvalues, loadings and principal components. Hotelling T^2 statistics was calculated for each row of principal component. Principal component plot shows the two groups of individuals of normal bearing and fault bearing. The Hotelling T^2 shows a shift from normal bearing to fault bearing. Principal components combined with Hotelling T^2 was able to detect fault bearing from normal bearing. The proposed method can be used as a tool in bearing diagnostic combined with other technique.

2. LITERATURE REVIEW

The main objective of principal component analysis is to seek a standardized linear combination with maximal variance (Mardia, Kent, and Bibby 1979). One question which can be asked concerning the data is how the results on different measurements should be combined to produce an overall score. Principal component analysis looks for a few linear combination which can be used to summarize the data. Principal component analysis has been presented in a variety way. A geometrical view through duality diagram was proposed to present the multivariate data analysis (Holmes 2008). The multivariate data consist of n individuals and p variables represented by a triplet (***X***,***Q***,***D***), where ***D*** is an $n \times n$ diagonal matrix of weights on the observations. In the simple case $\mathbf{Q}$ is a diagonal matrix defining the scale of different variables $\mathbf{Q} = \mathrm{diag}\left(\frac{1}{s_i^2}, i = 1,2,\ldots,p\right)$. In general case $\mathbf{Q}=\mathbf{L}^T\mathbf{L}$ where ***L*** is a *p x p* matrix of rank p which can viewed as a linear transformation of ***X*** such that ***Y*** = ***XL***. As the approach is geometrical, ***Q*** and ***D*** define inner products in $\mathbb{R}^p$ and $\mathbb{R}^n$:

$$\mathbf{x}^T\mathbf{Q}\mathbf{y} = \langle \mathbf{x},\mathbf{y}\rangle_{\mathbf{Q}}, \mathbf{x},\mathbf{y} \in \mathbb{R}^p \quad \ldots (1)$$

$$\mathbf{v}^{\mathbf{T}}\mathbf{D}\mathbf{w} = \langle \mathbf{v},\mathbf{w}\rangle_{\mathbf{D}}, \mathbf{v},\mathbf{w} \in \mathrm{R}^{n} \quad \text{... (2)}$$

When a researcher collects a multivariate data, generally there are two objectives: the comparison of variables, and the comparison of the individuals. An operator from the space of observations R^{p} onto the dual summarized by defining ***V*** and ***W*** as $\mathbf{V} = \mathbf{X}^{\mathrm{T}}\mathbf{D}\mathbf{X}$ and $\mathbf{W} = \mathbf{X}\mathbf{Q}\mathbf{X}^{\mathrm{T}}$. The covariance $\mathbf{V}\mathbf{Q} = \mathbf{X}^{\mathrm{T}}\mathbf{D}\mathbf{X}\mathbf{Q}$ is called the characterizing operator. Multivariate data analysis considered the triplet $(\mathbf{X},\mathbf{Q},\mathbf{D})$ to describe the data and its use either covariance or correlation. The dispersion of individuals mainly concerns with the operator $\mathbf{W}\mathbf{D} = \mathbf{X}\mathbf{Q}\mathbf{X}^{\mathrm{T}}\mathbf{D}$. The mapping of the individuals in the space spanned by the principal components will give a way for studying the likeness of the individuals. Let $\mathbf{S} = \mathbf{Y}^{\mathrm{T}}\mathbf{D}\mathbf{Y}$ the covariance matrix of $\mathbf{Y} = (\mathbf{I} - \mathbf{1}\mathbf{D}\mathbf{1}^{\mathrm{T}})\mathbf{X}$ and $\{(\lambda_{\alpha},\mathbf{z}_{\alpha}), \alpha = 1,\ldots,\mathrm{p}\}$ the eigenvalues and the eigenvectors of ***S*** ; $\mathbf{S}\mathbf{z}_{\alpha} = \lambda_{\alpha}\mathbf{z}_{\alpha}, \mathbf{z}_{\alpha}\mathbf{z}_{\beta} = \delta_{\alpha\beta}, \alpha,\beta = 1,\ldots,\mathrm{p}$. The linear combination of ***Y*** $\{(\psi^{\alpha} = \mathbf{Y}\mathbf{z}_{\alpha}/\sqrt{\lambda_{\alpha}}), \alpha = 1,\ldots,\mathrm{p}\}, (\psi^{\alpha})^{\mathrm{T}}\mathbf{D}\psi^{\alpha} = \delta_{\alpha\beta}$ are the principal components of ***S***. The principal components are the vector eigen of ***WD***; $\mathbf{W}\mathbf{D}\psi^{\alpha} = \mathbf{X}\mathbf{Q}\mathbf{X}^{\mathrm{T}}\mathbf{D}\psi^{\alpha} = \lambda_{\alpha}\psi^{\alpha}$. The dispersion of the individuals lies in the principal components of $(\mathbf{X},\mathbf{Q},\mathbf{D})$, the information is given by the eigenvalues and eigenvectors of the operator $\mathbf{W}\mathbf{D} = \mathbf{X}\mathbf{Q}\mathbf{X}^{\mathrm{T}}\mathbf{D}$ called operator related to the study $(\mathbf{X},\mathbf{Q},\mathbf{D})$. The eigen systems $\{(\lambda_{\alpha},\varphi_{\alpha} = (\mathbf{L}^{-1}\mathbf{z}_{\alpha})), \alpha = 1,\ldots,\mathrm{p}\}$ and $\{(\lambda_{\alpha},\psi^{\alpha}), \alpha = 1,\ldots,\mathrm{p}\}$ are related to the following barycentric equations:

$$\mathbf{X}^{\mathrm{T}}\mathbf{D}\mathbf{X}\mathbf{Q}\varphi_{\alpha} = \lambda_{\alpha}\varphi_{\alpha} \quad \text{... (3)}$$

$$\varphi_{\alpha}^{T}\mathbf{Q}\varphi_{\alpha} = \delta_{\alpha\beta} \quad \text{... (4)}$$

$$\psi^{\alpha} = \mathbf{X}\mathbf{Q}\varphi_{\alpha}/\sqrt{\lambda_{\alpha}} \quad \text{... (5)}$$

$$\varphi_{\alpha} = \mathbf{X}^{\mathrm{T}}\mathbf{D}\psi/\sqrt{\lambda_{\alpha}}\,. \quad \text{... (6)}$$

The usual practices of principal components analysis on the covariance and on the correlation are based on the best approximation

$$\mathbf{X}\mathbf{Q}\mathbf{X}^{\mathrm{T}}\mathbf{D} \approx \Psi^{[k]}\Lambda^{[k]}\left(\Psi^{[k]}\right)^{\mathrm{T}}\mathbf{D} \quad \text{... (7)}$$

$$\mathbf{X}^{\mathrm{T}}\mathbf{D}\mathbf{X}\mathbf{Q} \approx \Phi^{[k]}\Lambda^{[k]}\left(\Phi^{[k]}\right)^{\mathrm{T}}\mathbf{Q} \quad \text{... (8)}$$

where $\Psi^{[k]}$ and $\Phi^{[k]}$ are the first k columns of $\Psi = (\psi^{\alpha}, \alpha = 1,\ldots,\mathrm{p})$ and $\Phi = (\varphi_{\alpha}, \alpha = 1,\ldots,\mathrm{p})$ and $\Lambda^{[k]} = \mathrm{diag}(\lambda_{1},\ldots,\lambda_{\mathrm{k}})$.

The general distribution of quadratic form was initiated by Hotelling (Mardia, Kent, and Bibby 1979). The main results related to bearing diagnosis are summarized as follows. If α can be written as $m\mathbf{d}^{\mathrm{T}}\mathbf{M}^{-1}\mathbf{d}$ where ***d*** and ***M*** are independently distributed as $\mathbf{N}_{\mathbf{p}}(\mathbf{0},\mathbf{I})$ and $\mathbf{W}_{p}(\mathbf{I},m)$ then α has the Hotelling $T^{2}(p,m)$ distribution, $\alpha \sim T^{2}(p,m)$ \. The square of the univariate t_{m} has the $T^{2}(1,m)$ distribution. The $F_{1,m}$ distribution and the $T^{2}(1,m)$ distribution are the same, in general $T^{2}(p,m) = \{mp/(m-p+1)\}F_{p,m-p+1}$. If $\mathbf{X}$ and ***M*** are independently distributed as $N_{\mathrm{p}}(\eta\Sigma)$

and Wishart $W_p(S,m)$ then $m(\mathbf{x} - m)^T \mathbf{M}^{-1}(\mathbf{x} - m) \sim T^2(p,m)$. If $\overline{\mathbf{X}}$ and $\mathbf{S}$ are the mean vector and covariance matrix of a sample of size n from $\mathbf{N}_p(m,S)$ and $\mathbf{S}_u = (n(n-1))\mathbf{S}$ then $(n-1)(\mathbf{x} - m)^T \mathbf{S}^{-1}(\mathbf{x} - m) \sim T^2(p,n-1)$.

3. RESEARCH METHODS

The first step is to collect the vibration signal from the bearing using laboratory experiment. Accelerometer is used as sensing element in order to collect these vibration signal. The accelerometer provides a voltage that corresponds to the vibration level. Time domain is used to analyze the failure by analyzing the vibration signal obtained from the bearing. Feature extraction is the parameter which represent the peaks, shapes and randomness of the signal. Some of vibration signal that are used to diagnosis the bearing signal are mean, standard deviation, root mean square, peak value, kurtosis, skewness. The methodology suggested in this article is based mainly on data exploration using box plot, principal component analysis of bearing features and statistical process control using Hotelling T^2. The fault detection is regarded as pattern recognition problem where two classes introduced: the class of signals from healthy bearing and the class of signals from faulty bearing. The classification process has two steps: setting a threshold and comparison to the feature calculated from a signal under test, Hotelling T^2, to the threshold.

4. RESULTS AND DISCUSSION

The data file contains two types of bearing conditions; normal condition and fault condition, described by 12 variables. Qualitative variables such as rotation speed and loading would be considered as supplementary variables. If the data are collected following a random sampling, the same weight is allocated to each observation. Correlation matrix (Table 1) contains the linear correlation between all pairs of variables. It summarizes linear dependency between the p variables. The interpretation is based on distance between points representing individuals. Principal component analysis provides graphical representation allowing the visualization of relations between variables and the existence of groups of individuals. Principal component analysis results are two-dimensional figures, and the interpretation is the most delicate phase of the analysis. In this study, the first principal plane shows a group individual for the case of normal bearing and two groups of individuals for the case normal and fault bearing. The aim is to see how the observations are scattered, which observations are similar, which observations differ from the other. Opposite individuals used to interpret the principal axes.

A control chart is a tool which allows a shift of a mean through successive samples. The detection of process shift can be detected using control chart. In most of the cases there are not one but several characteristics to control. The usual practice consists of using as many charts as characteristics. This practice leads to undesired situation of false alarm. The univariate charts may signal out of control while multivariate process is under control. To summarize the data information, not only the first component should be retained but also the last components considered as residual of the analysis. In process control, principal components is used as a method for detecting shift considered as outliers. The last principal components may be as interesting as the first component. Principal components are defined as linear combinations of variables take into account the correlation structure and used to detect shift. It is possible to find interpretation for the principal components based on small number of variables among the original variables. The control chart of first and last component is proposed as a method to improve the shift detection. Projection pursuit has been proposed as a tool for the interpretation of principal components.

Figure 1 shows the box plot for normal bearing and Figure 2 shows the box plot for faulty bearing. It can be observed that a significance pattern of these two box plots. Figure 3 shows bearing standard deviation and Figure 4 shows the root mean square of bearing vibration. The figures show increased variation at the end of period of observation which indicates the state of bearing. Figure 5 shows the projection of bearing vibration in two-dimensional space. It can be observed that the first two components capture most of the variation in higher dimensional data. Figure 7 shows the results of Hotelling T^2 statistic to detect a shift from normal to fault bearing. It can be seen that normal bearing lies below the threshold while fault bearing lies above the threshold. Hotelling T^2 statistic measures systematic variation of the process, and if there are violations it will indicate that systematic variations are out of control. Principal component Hotelling T^2 can successfully detect bearing fault as shown in Figure 5, Figure 6 and Figure 7.

Table 1. Correlation Matrix

	max	min	avrg	stddev	rms	skewness	kurtosis	peak	crest	shape	var	range
max	1.000											
min	-.221	1.000										
avrg	-.122	.239	1.000									
stddev	.277	-.349	-.713	1.000								
rms	.195	-.301	-.958	.885	1.000							
skewness	.189	.282	-.145	.139	.154	1.000						
kurtosis	.255	-.345	.371	-.424	-.420	-.315	1.000					
peak	1.000	-.221	-.122	.177	.195	.189	.255	1.000				
crest	-.872	-.072	.359	-.161	-.305	.109	.459	.872	1.000			
shape	-.147	.063	-.609	-.119	.356	.055	-.073	-.147	-.333	1.000		
variance	.274	-.341	.690	.998	.864	.141	-.437	.274	-.157	-.148	1.000	
range	.709	.844	-.239	.404	.325	-.100	.390	.709	.531	-.126	.396	1.000

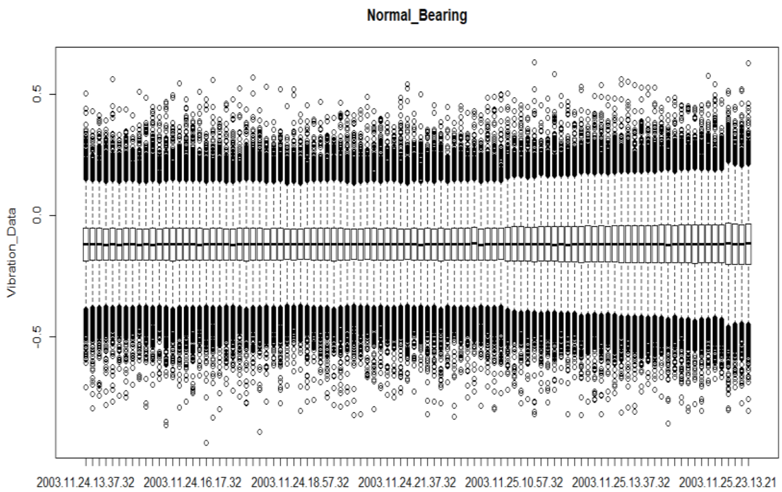

Figure 1. Box Plot Normal Bearing

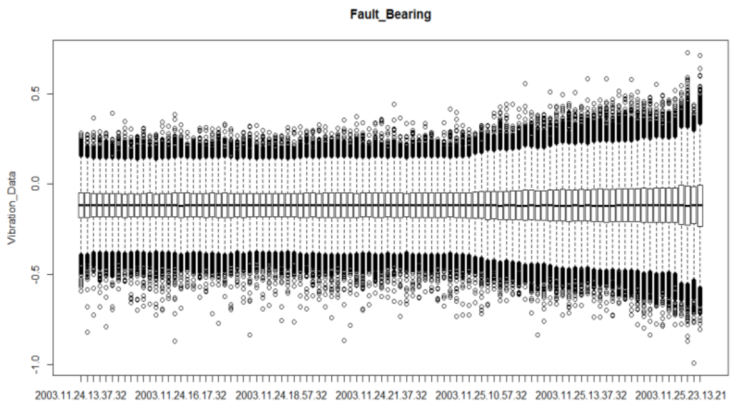

Figure 2. Box Plot Fault Bearing

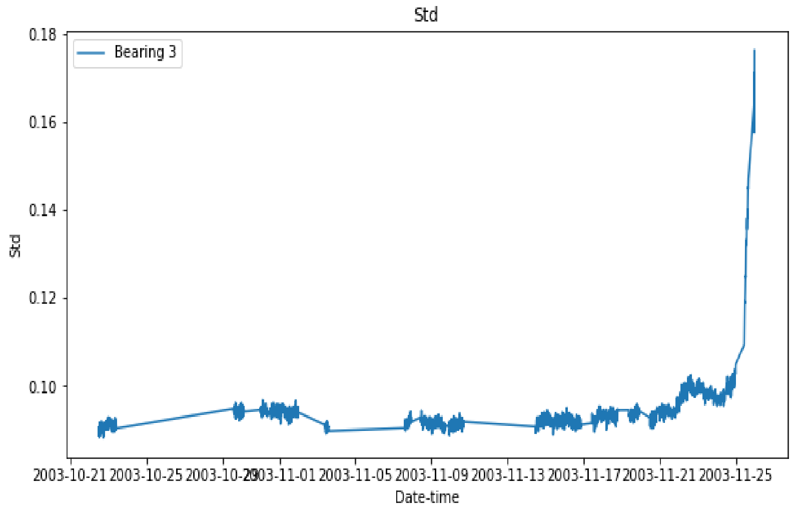

Figure 3. Bearing Standard Deviation

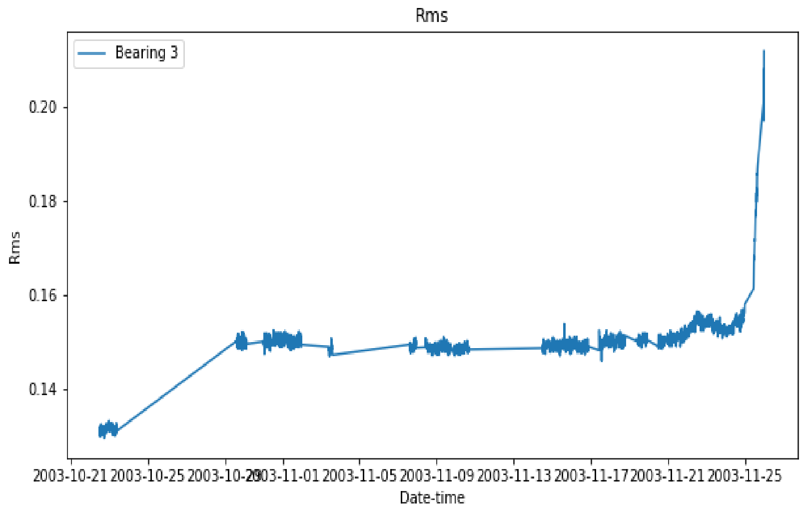

Figure 4. Root Mean Squares (RMS)

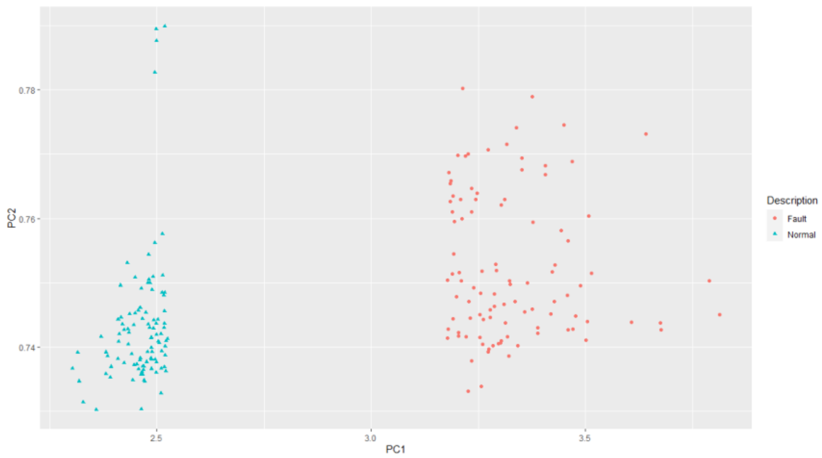

Figure 5. Plot of Two Principal Component

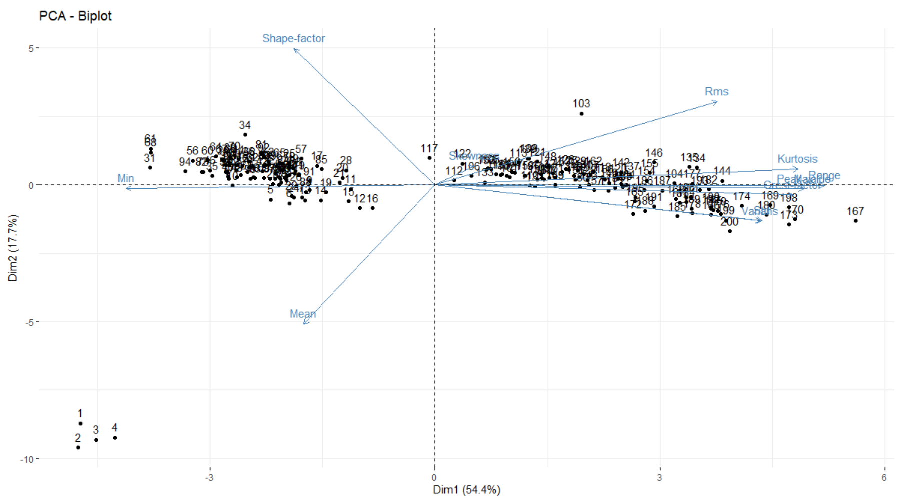

Figure 6. Biplot of Two Principal Components

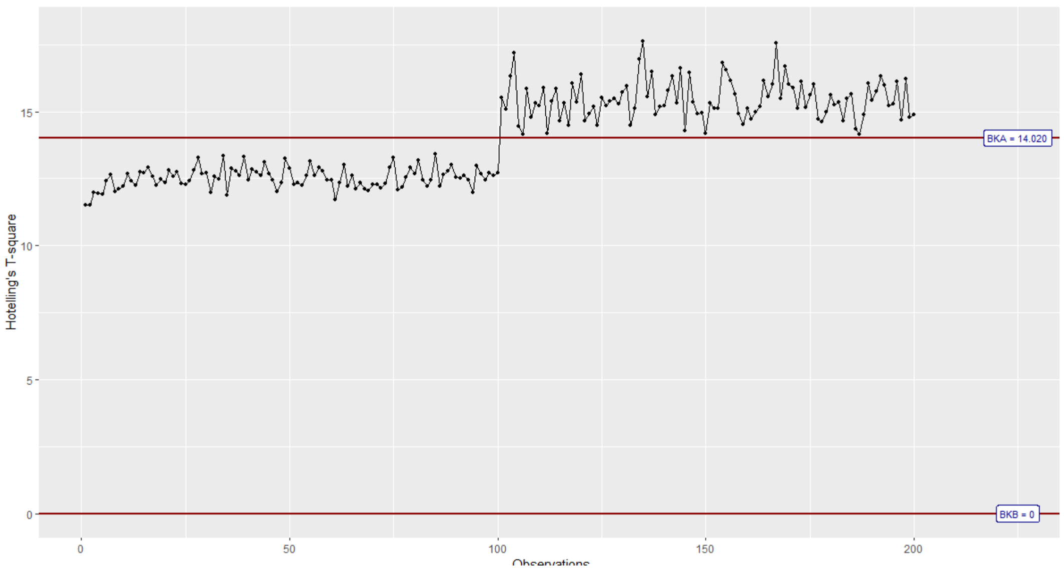

Figure 7. T-square of Normal Bearing and Fault Bearing

5. CONCLUSIONS AND SUGGESTIONS

The principal components and Hotelling T^2 are combined and used as a tool in bearing diagnostic. Application of the method on normal dan fault bearing shows that the proposed method was able to detect a shift from normal to fault bearing. The proposed method can used as a tool in bearing diagnostic. The principal component Hotelling T^2 should be compared with ordinary Hotelling T^2 to show the capability of these two methods. Extension to multi faults should be investigated in the future.

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