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# Dimensions reduction of vibration signal features using LDA and PCA for real time tool wear detection with single layer perceptron

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# Dimensions reduction of vibration signal features using LDA and PCA for real time tool wear detection with single layer perceptron.

**Anis Arendra[1], Herianto Herianto[2], Sabarudin Akhmad[3] and Ida Lumintu[3]**

[1] Department of Mechanical Engineering, University of Trunojoyo Madura, Jl. Raya Telang, Bangkalan, Madura 69162 Indonesia

[2] Department of Mechanical & Industrial Engineering, University of Gadjah Mada Indonesia. Jl. Grafika 2, Yogyakarta 55281 Indonesia

[3] Department of Industrial Engineering, University of Trunojoyo Madura, Jl. Raya Telang, Bangkalan, Madura 69162 Indonesia

Email: anis.arendra@trunojoyo.ac.id

**Abstract**. This study uses the Linear Discriminant Analysis (LDA) method along with the Principal Component Analysis (PCA) method to reduce the dimensionality of the vibration signal feature classified by Single Layer Perceptron (SLP). The vibration features to be reduced are 10 out of 270 features selected based on the correlations analysis. The LDA and PCA transformations provide only three inputs, than the original 10 signal features for the SLP classifier. The Single Layer Perceptron is trained with a sequential incremental training approach using the perceptron learning rule. The training phase of SLP resulting Mean Squared Error (MSE) as low as 0.0840 and the validation phase in the CNC machining provides 97.5% accuracy with zero false alarms.
Keywords: *Tool Wear Detection, Principal Component Analysis, Single Layer Perceptron, Linear Discriminant Analysis*.

## 1. Introduction

The vibration signals of machining are so large dimensions generally. Problems with the pattern recognition on high dimensionality will greatly loading the computation of the classifier and reduce performance due to noisy signal[1][2][3]. The advantages of using dimensions reduction techniques are[2] reducing classifier training time, facilitating data visualization, preventing overtrained, speeding up classifier processing time, and reducing data storage. Some dimensions reduction techniques commonly used in signal classification research[1] are: Principal Components Analysis[4][5], Linear Discriminant Analysis[6], Maximum Variance Unfolding[7] Manifold charting[8], Local Tangent Space Analysis[1][7], Laplacian Eigenmaps[9], Isomap[10], Multidimensional Scaling[1], Hessian LLE[11]. Dimension reduction is performed with the objectives of selecting the subset of features without losing much valuable information.

## 2. The objective of research and method of research

The purpose of this research is to reduce the features dimensionality in the tool wear classification using LDA and PCA transformations. The signal data used for the classification of tool wear are vibration signals during CNC milling operations. The vibration signal features to be reduced are 282 features, 12 features of which are from the time domain features and 270 features of which are the order domain vibration features. Before the vibration features is reduced, the features is selected based on the regression analysis. Only features with a coefficient of regression above 0.5 are selected. Dimension reduction is perform using PCA and the main principal components selected. Then, the dimension reduction is perform using LDA and the main canonical components selected. The outputs of the principal transformation and the canonical transformation are passed on to the tool condition classifier. The classifier used in this research is the single layer perceptron (SLP). This single layer perceptron is then trained and tested to classify tool conditions in realtime during CNC milling operations based on its vibration.

## 3. Related work

Hoffmann[4] has developed a new method, combined dimension reduction using the PCA kernel with SVM classifier for the case of freehand line recognition. Cheng and Lu[12] have developed a combined Scoring System Based on Sampling Survey Method with Heuristic Intelligent Optimization Algorithm for the case of vehicle vibration recognition and the case of gene-selection in bioengineering. Hughes dan Tarassenko[13] formed the ECG Shape Descriptor using wavelet transform for dimensional fetures reduction. Triwiyanto, et.al.[14] has developed a Kalman filter model for estimating elbow angles based on EMG signals.
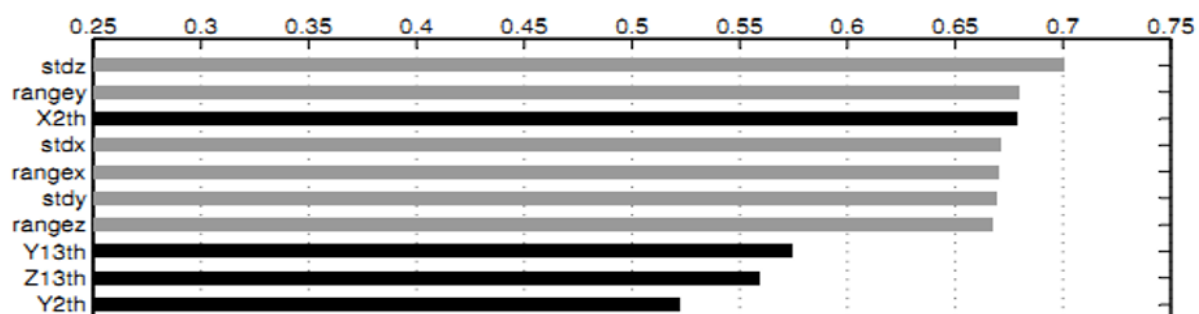


**Figure 1.** The vibration features with coefficient of correlation greater than 0.5.

## 4. Results and discussion

### 4.1. Vibration signal features

The 270 vibration signal features are arranged in row matrix as in the equation 1. This features consists of first order spectrum to $90^{th}$ order spectrum of X-axis, Y-axis, Z-axis vibrations and the time domain statistical features. There are a total of 1800 columns data of vibration feature sample recorded from the machining vibrations of the CNC milling. The 270 feature signals are selected before reducing the dimensionality of features. Feature selection is based on regression analysis of vibration features. The ordering of features with the highest correlation coefficient is shown in the figure 1. Based on the correlation analysis, 10 features were selected that had a correlation coefficient of more than 0.5, are X2th, Y13th, Z13th and Y2th of order domain and stdz, rangey, stdx, rangex, stdy, and rangez of the time domain.

$$
\begin{aligned}
FeaturesAndLabel_i = (X1th \quad &X2th \ ... \ X90th \quad Y1th \quad Y2th \ ... \ Y90th \quad Z1th \quad Z2th \ ... \quad Z90th \ ... \\
&stdxi \quad skewxi \quad kurtxi \quad rangexi \ stdyi \quad skewyi \quad kurtyi \quad rangeyi \ ... \\
&stdzi \quad skewzi \quad kurtzi \quad rangezi \ Label_i \ ) \qquad\qquad\qquad ...eq(1)
\end{aligned}
$$

## 4.2. Features dimension reduction using Principal Component Analysis

The dimension reduction uses PCA by combining 4 domain order features and 6 time domain features so that 10 principal features are obtained. Principal component analysis is performed to find the principals direction of the largest variants of ten features based on 1800 available sample data. The distribution patterns of the worn tool and normal tool sample data in the three main principals direction seen in the figure 2. The 6 out of 10 principal components distribution of variants is shown in figure 3. From the Pareto diagram, the contribution of the first principal variant did not reach 70%. But the first principal along with the second principal contributed more than 80% variants while less than 20% of the remaining variants were distributed in the next 8 principals
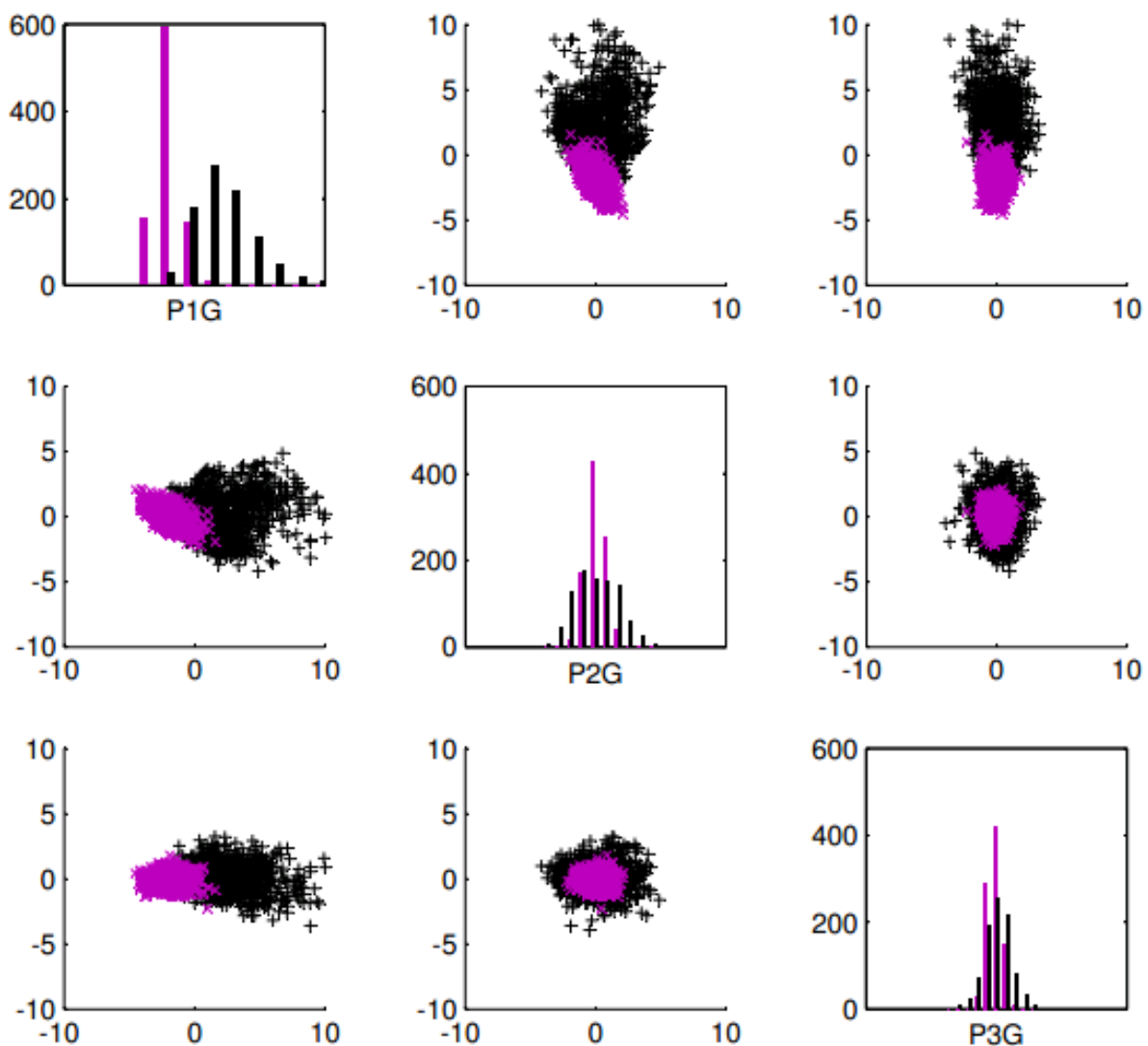


**Figure 2.** The distribution patterns of the worn tool and normal tool sample data in the three main principals direction.
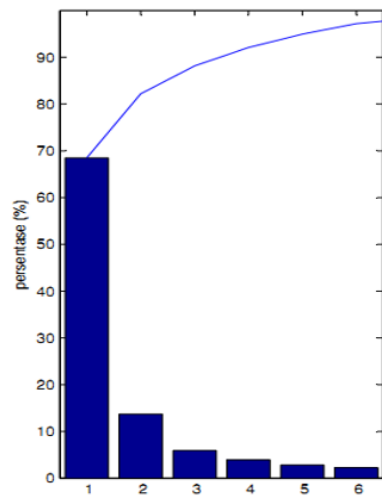
**Figure 3.** The Pareto diagram of principal components distribution of variants.

*4.3. Features dimension reduction using Linear Discriminant Analysis*

The linear discriminant analysis performs feature transformation to find the canonical direction based on the best degree of class separation. The distribution pattern of sample data for normal tools and worn tools based on the first and second canonical transformation is shown in the figure 4.
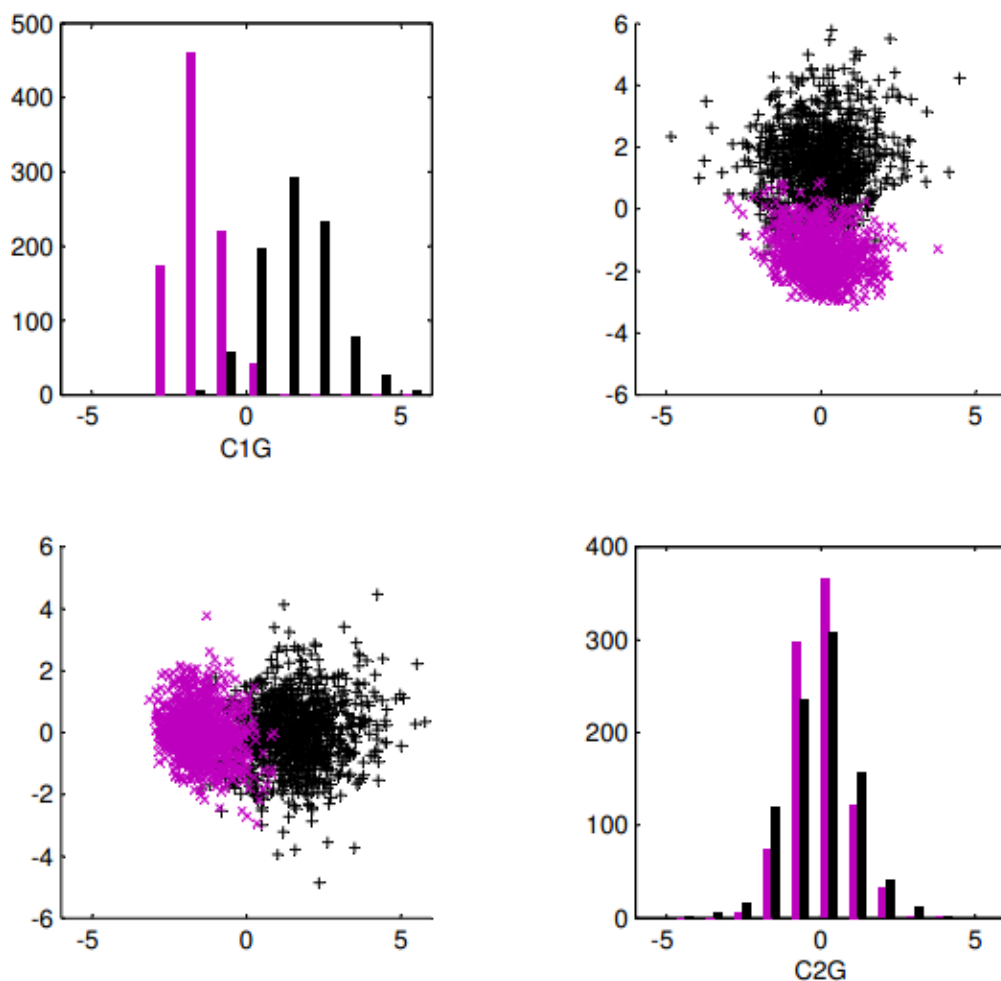


**Figure 4.** The distribution patterns of the worn tool and normal tool sample data in the first and second canonical direction.

### 4.4. Feature transform

The PCA and LDA transformation of 10 features gets 3 new features: combined Principal component 1 (P1G), combined Principal component 2 (P2G), and combined Canonical component 1 (C1G). This new transformed feature is a linear combination of the previous features with the transformation matrix of equation 2.

$$[P1G \quad P2G \quad C1G] = [F1 \quad F2 \quad \dots \quad F10] \begin{bmatrix} 0,342 & -0,19 & 1,726 \\ 0,311 & -0,32 & 0,859 \\ 0,341 & -0,22 & -0,11 \\ 0,319 & -0,26 & 0,485 \\ 0,344 & -0,09 & -1,58 \\ 0,317 & -0,33 & -0,36 \\ 0,262 & 0,389 & 1,021 \\ 0,351 & 0,388 & -0,22 \\ 0,306 & 0,432 & 0,239 \\ 0,251 & 0,367 & 0,090 \end{bmatrix} \dots eq(2)$$

### 4.5. Single layer perceptron classifier

Single layer perceptron training (SLP) iteration uses the perceptron learning rule algorithm with the weight adaptation approach in sequential incremental training for 1800 randomized sample data. A summary of the training results is shown in the table 1.

**Table 1.** Summary of performance of the single layer perceptron classifier.

| Training | | Test | | | Validation | | |
|---|---|---|---|---|---|---|---|
| SLP Iteration | MSE | Missed | False Alarm | Accuracy | Missed | False Alarm | Accuracy |
| 1st | 0,0889 | 17,5% | **0,0%** | 90,6% | 5,0% | 0,0% | 97,5% |
| 2nd | 0,0895 | 17,2% | 1,1% | **91,1%** | 5,0% | 0,0% | 97,5% |
| 3th | 0,0889 | 18,1% | 0,0% | 90,6% | 5,0% | 0,0% | 97,5% |
| 4th | 0,0883 | 21,3% | 1,0% | 90,0% | 5,0% | 0,0% | 97,5% |
| 5th | 0,0895 | 18,0% | **0,0%** | **91,1%** | 5,0% | 0,0% | 97,5% |
| 6th | 0,0901 | 17,4% | **0,0%** | **91,1%** | 5,0% | 0,0% | 97,5% |
| 7th | 0,0883 | 20,2% | 1,0% | 90,0% | 5,0% | 0,0% | 97,5% |
| 8th | 0,0846 | 26,1% | **0,0%** | 86,7% | 5,0% | 0,0% | 97,5% |
| 9th | **0,0840** | 24,0% | 2,4% | 86,1% | 5,0% | 0,0% | 97,5% |
| 10th | 0,0889 | **12,8%** | 5,8% | 90,6% | 5,0% | 0,0% | 97,5% |
| | | | | | | | |
| **Best** | **0,0840** | **12,8%** | **0,0%** | **91,1%** | 5,0% | 0,0% | 97,5% |
| **Mean** | 0,0881 | 19,3% | 1,1% | 89,8% | 5,0% | 0,0% | 97,5% |
| **Worst** | 0,0901 | 26,1% | 5,8% | 86,1% | 5,0% | 0,0% | 97,5% |

## 5. Conclusion and future work

This study succeeded in achieving validation accuracy of 97.5% with a missed rate of 5.0% and 0% false alarm. The best Single Layer Perceptron training MSE of 0.0840 achieved in the 9th iteration. However, the best MSE in the training iteration is not followed by high testing accuracy, in that 9th iteration actually provides the lowest testing accuracy. The best testing accuracy of 91.1% was obtained in 2nd iteration, 5th iteration and 6th iteration with 0.0895, 0.0895 and 0.0901 MSE of training respectively.

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