# Data Extraction and Classification of Machined Module Surface Structure Images Using Artificial Intelligence Techniques

Dipika Mahale[1]
Ravindra Sonyabapu Shelke[2]
[1] PG Scholar, Mechanical Engineering, SVIT Nashik, Maharashtra, India
[2]Asst. Prof. Mechanical Engineering, SVIT Nashik, India

## ABSTRACT

*In recent era use of artificial intelligence techniques for texture analysis of machined surface is gaining importance in the field of manufacturing. The developed vision system uses a CCD camera for scanning gray-scale images from an area of the machined workpiece Captured images of machined surface using Electric discharge machining, milling, sand blasting and shaping is decomposed in to sub images and then discrete wavelet transform is applied on the sub images. To select the base wavelet minimum permutation entropy criterion is applied and statistical features were calculated from the base wavelet. Training and testing of feature vector is performed using two artificial intelligence techniques support vector machine and artificial neural network for identifying textured surface images. training identification of textured images is obtained using support vector machine and artificial neural network testing identification of textured images is obtained using support vector machine and artificial neural network respectively. Results revealed that the present methodology identifies machined surface images with high accuracy.*

.

**Keyword** -***texture characterization; wavelet; support vector machine; artificial neural network***

---

## 1. INTRODUCTION

One of the important characteristics of any image in mechanical surfaces by different machine operation is Surface texture. Many researchers are studying to classify the different texture data by analyzing the images of the different machined surfaces using machine vision. There are an ample variety of applications of digital image processing using machine vision in machining processes such as work piece surface texture measurements. This technique has become the topic of interest because of its non-contact and online application. Machine operations like shaping [1], [2], milling [3], and grinding [4] the surface texture of machined surface images was evaluated by digital image processing. For texture analysis model-based techniques were used. In present condition, quality control as well as the performance testing of mechanical component plays an important role in the manufacturing and production. In the current study, a non-contact method using computer vision for identification of the surface texture using varying manufacturing processes like EDM, shaping, milling and sandblasting has been consider. In manufacturing applications, surface finish is a key parameter and surface metrology is used to evaluate surface texture. The method includes the study of surface texture and their correlation to the manufacturing processes which produces the component and evaluates roughness/texture of the component. To identify texture images from machining processes, Artificial Intelligence emerge as a promising technique. It has been used for classification or identification in the different fields like Fault diagnosis, EEG signals, manufacturing etc. Support Vector Machine, Artificial Neural Network, Naive Bayes, Random Forest are widely used techniques for classification of data.

## 2. METHODOLOGY

In the conventional approach for a given texture analysis various signal processing techniques are used to analyze texture images. Discrete Wavelet Transform (DWT) is another technique which is used to extract the wavelet coefficients from different mother wavelet functions. Since manufacturing processes are generally complex in nature therefore complexity/uncertainty plays a significant role. In recent years Shannon entropy (SE) and Multiscale permutation entropy (MPE) emerges as a strong measure to detect the irregularity present in the signal. After comparing the values over multiple scales results revealed that MPE is useful to select the base wavelet [5] while Shannon entropy is useful for evaluation of the complexity of wavelet coefficients based on a single scale.

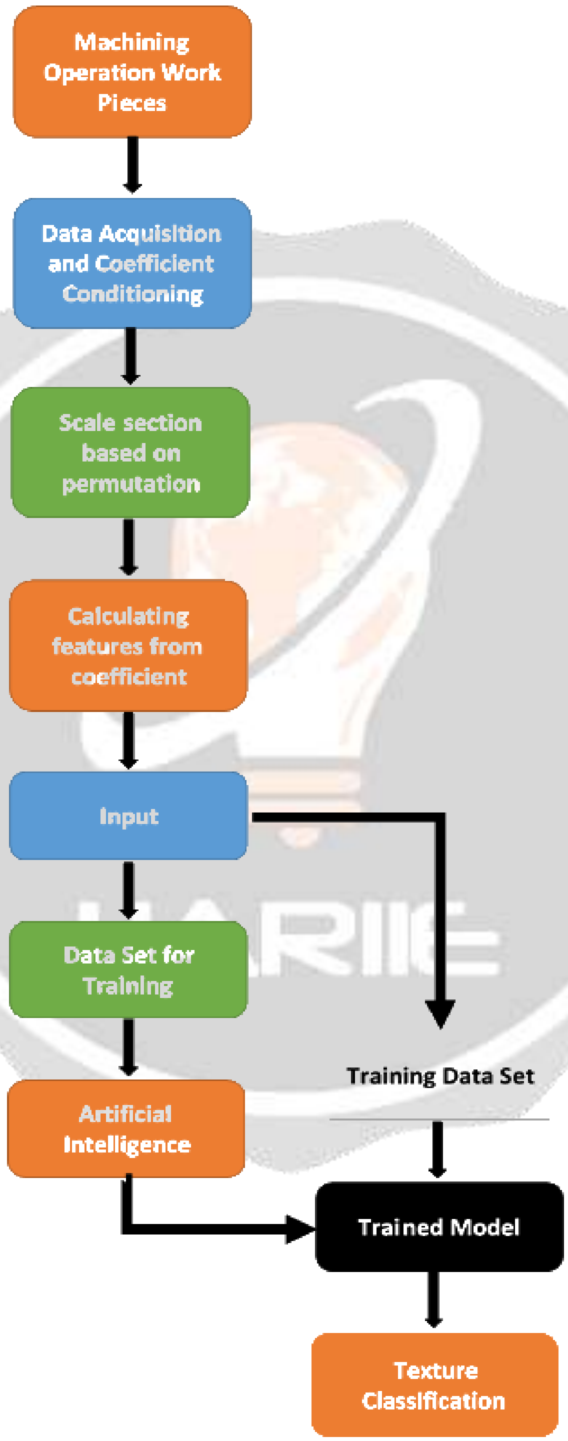


**Fig -1**: Surface Structure recognize methodology

## 3. EXPERIMENTAL SETUP

Experimental set-up for capturing texture images includes CCD camera, Image processor LC processing hardware with 4 frame buffers, Pulnix -TM6 and 1/30 s as a grabbing speed The schematic diagram is shown in fig. 2. Work piece is illuminated by a white light source which is inclined at 45o with the respect to work piece surface. Industrial interface is used to convert captured image into a digital image and the processed image was displayed on the monitor. The current study was carried out to identify machined surfaces obtained by applying different machining operations like Milling, Shaping, Sandblasting and EDM. Different surface textures images were obtained after capturing from CCD camera.

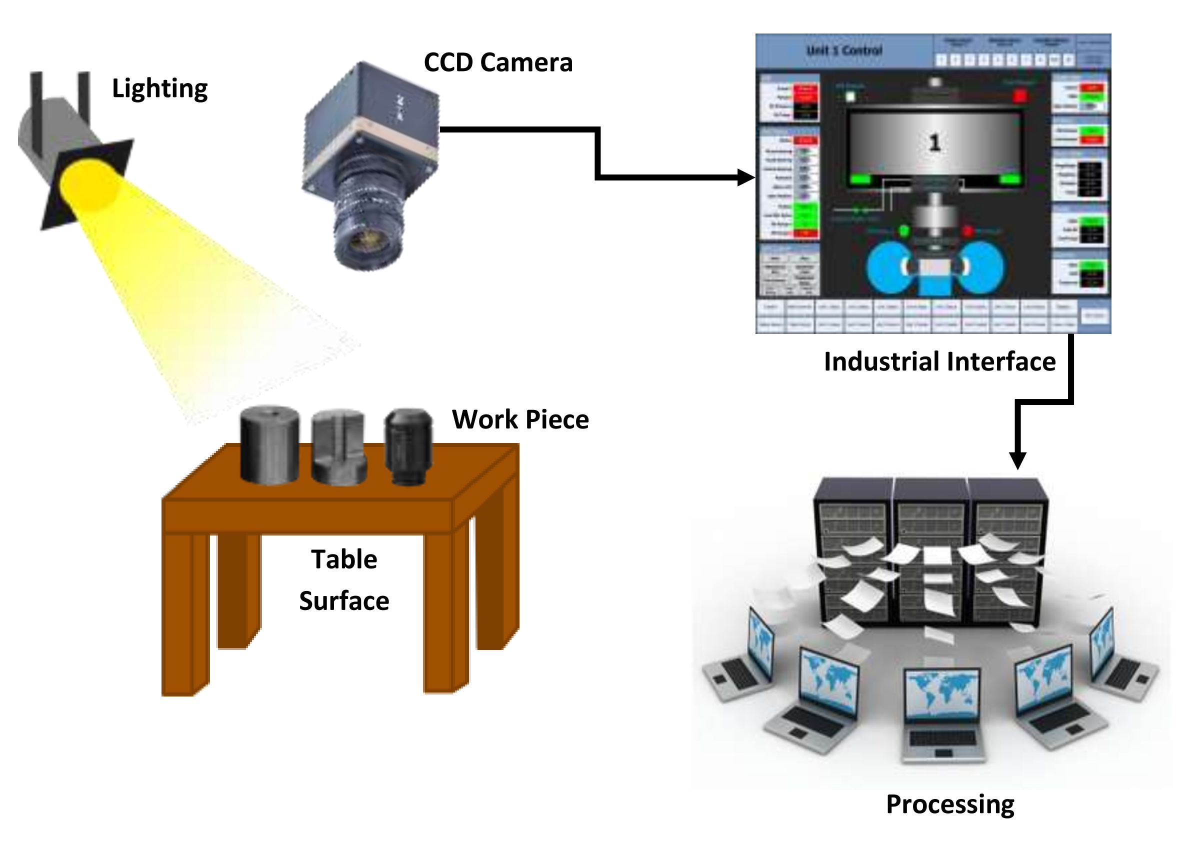


**Fig -2**: Experiment setup

## 4. FEATURES EXTRACTION

In the present study, the original image of machined component is subdivided into 16 equal parts having non overlapping images and then it is pre-processed by converting into gray scale through continuous 2D wavelet transform. Seven base wavelets viz. Symlets, Coiflets, Daubechies, Haar, Morlet, Reverse Biorthogonal and Biorthogonal are used to extract coefficients from Discrete Wavelet Transform (DWT) at the first level of decomposition (21 scales). Minimum permutation entropy criterion is applied to select the base wavelet. The coefficient which gives minimum permutation entropy was chosen and the different statistical features are calculated. Haar wavelet coefficients are selected since it is giving least permutation entropy. Twenty statistical features like Mean, Median, Maximum, Minimum, Range, Median Absolute, Standard Deviation, Mean Absolute Deviation, L1 norm, L2 norm, Maximum norm, Permutation Entropy, Energy, Shannon Entropy, Maximum Energy to Entropy Ratio, Log Energy Entropy, Sure Entropy, Threshold Entropy and Maximum relative Energy are extracted from wavelet coefficients obtained from the images of each machine operation.

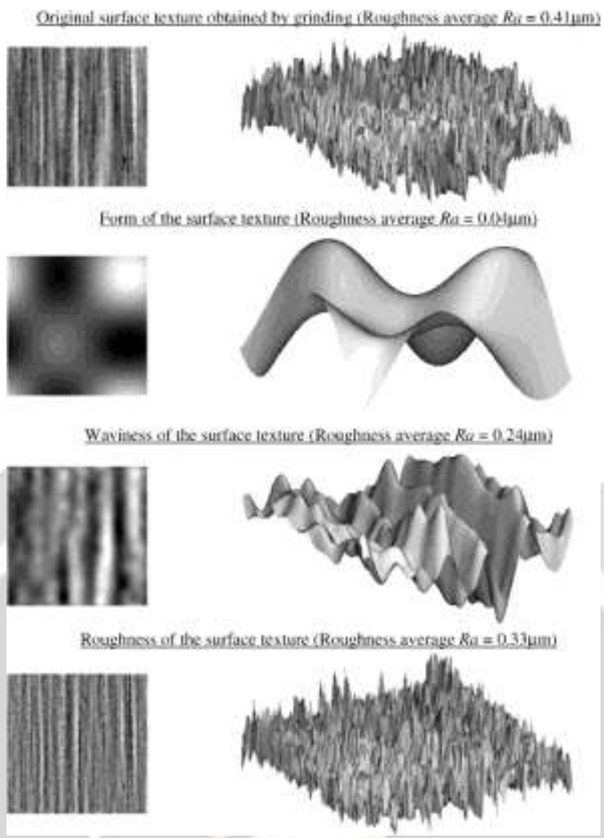


**Fig -3** Image of different machine operations

## 5. ARTIFICIAL INTELLIGENCE TECHNIQUE

A. Artificial Neural Network

Artificial neural network (ANN) has been developed and used for classification purpose. ANNs consist of interrelated processing elements known as neurons and it is adaptively changing its structure during learning stage [5]. ANN is a type of supervised learning method used for classification of features. Radial basis, multilayer perceptron are the types of methodologies used in ANN. In ANN weights are amend, for error minimization between ANN predictions and outputs.

B. Support Vector Machine

In 1998, Vapnik introduced a new statistical learning method based on the principle of structural risk minimization. A learning machine has prearranged several set of features with class labels and it's a supervised learning algorithm. In SVM, the optimal hyper plane separating the data can be obtained as a solution to the following optimization problem

$$Minimize \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{M}\xi i \qquad (3)$$

subject to

$$y_i(w' x_i + b) \geq 1 - \xi i \qquad (4)$$

$$i = 1,2,\ldots M$$

## 6. DISCUSSION

To identify texture surfaces of machined component Artificial Neural Network and Support Vector Machine techniques are applied on the features obtained through different machine operations like EDM, sandblasting, shaping and Milling. For illustration purpose, a sample feature vector (random) consisting of twelve features and four classes is shown in Table I. Total 64 instances are obtained from the four classes each class consist of 16 images. Training and Testing of feature vector is performed and evaluated using Artificial Intelligence technique. Table II shows the texture characterization efficiency using SVM and ANN. It is observed that both SVM and ANN gives 100 % texture characterization efficiency using training. When testing is performed on the feature vector then ANN gives 100 % texture characterization efficiency while SVM gives 87.5 % texture characterization efficiency. For testing of feature vector, one fourth of the whole data set has been taken as testing data. Table III shows the confusion matrix obtained when ANN is used as a classifier. It is clear that all classes are predicted correctly by ANN both for training and testing of data set. Table IV shows the confusion matrix obtained when SVM is used as a classifier. It is observed that SVM is able to identify all classes correctly when training on feature vector is performed, giving 100 % accuracy. For testing of feature vector SVM is able to identify three instances correctly out of four instances. Similarly, for Milling, SVM is able to identify two instances correctly out of three instances.

## 7. CONCLUSION

In the present methodology for texture characterization of machined surfaces, seven wavelets coefficients are compared and minimum permutation entropy criterion is applied to select the base wavelet. Haar wavelet is selected as a base wavelet and the coefficients obtained are used for calculation of twenty statistical features. Training and testing of feature vector is performed using SVM and ANN. It is observed form the result that ANN gives better texture characterization efficiency as compared to SVM. Based on the result obtain the proposed methodology is useful to characterize texture surfaces with high accuracy.

## 8. REFERENCES


[01] C. Bradley and Y. S. Wong, “Surface texture indicators of tool wear - a machine vision approach,” Int. J. Adv. Manuf. Technol., vol. 17, no. 6, pp. 435–443, 2001.

[02] X. Zhang, C. Krewet, and B. Kuhlenkötter, “Automatic classification of defects on the product surface in grinding and polishing,” Int. J. Mach. Tools Manuf., vol. 46, no. 1, pp. 59–69, 2006.

[03] V. Vakharia, V.K. Gupta, P.K. Kankar, “A comparison of feature ranking techniques for fault diagnosis of ball bearing”, Soft Computing, vol. 20 no.4,pp. 1601–1619, 2016.

[04] Z. Ma, J. Y. Leung, and S. Zanon, “Integration of Artificial Intelligence and Production Data Analysis for Shale Heterogeneity Characterization in SAGD Reservoirs,” in SPE Canada Heavy Oil Technical Conference, 2016, pp. 1–14.

[05] K. Venkat Ramana and B. Ramamoorthy, “Statistical methods to compare the texture features of machined surfaces,” Pattern Recognit., vol. 29, no. 9, pp. 1447–1459, 1996.

[06] C. Bandt and B. Pompe, “Permutation entropy: a natural complexity measure for time series.,” Phys. Rev. Lett., vol. 88, no. 17, p. 174102, 2002.

[07] LB Jack, AK Nandi. Fault detection using support vector machines and artificial neural networks, augmented by genetic algorithms [J]. Mechanical Systems & Signal Processing, 2002, 16 (2-3): 373-390.

[08] Gadelmawla ES, Koura MM, Maksoud TMA, Elewa IM, Soliman HH. Using the grey level histogram to distinguish between roughness of surfaces. Proc I MECH E, Part B, J Eng Manuf 2001;215(4): 545–53.

[09] Kiran MB, Ramamoorthy B, Radhakrishnan B. Evaluation of surface roughness by vision system. Int J Mach Tools Manuf 1998;38(5-6): 685–90.

[10] Lee BY, Juan H, Yu SF. A study of computer vision for measuring surface roughness in the turning process. Int J Adv Manuf Technol 2002;19:295–301.