Reducing Image Size and Noise Removal in Fast Object Detection using Wavelet Transform Neural Network

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Abstract: A robot detects its surroundings through camera information and its response requires a high-speed image process. Due to the increasing application of vision systems, various algorithms have been developed to increase speed of image processing. This paper proposes a double density Discrete Wavelet-based Neural Network to enhance feature extraction and classification of parts in each picture. The Discrete Wavelet-based Neural Network combines multi-scale analysis ability of the wavelet transform and the classification capability of the artificial neural network by setting the wavelet function as the transfer function of the neural network. The automatic assembly process needs to capture the image in an online process in order to recognize the parts in the image and identify the location and orientation of the parts. In this part, the two dimensional double density discrete wavelet transform have been applied to compress and remove noise from the captured Image. By applying a value for the threshold, the coefficients of the wavelet transform function are obtained using these coefficients and the characteristics of the wavelet coefficients are calculated. Subsequently, a multilayer perceptron is trained using these extracted features of the images. To find the best vector characteristics, various combinations of extracted properties have been investigated. This method has succeeded in object detection and results show that the Neural Networks and the training algorithm based on the wavelet transform function have exquisite accuracy in classification. Thus, the developed method is considered effective as compared to other state-of-the-art techniques.

Keywords: Feature Extraction, Image Compression, Neural Network, Object Detection, Wavelet Transform

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1 INTRODUCTION

The automatic assembly needs to estimate the pose and orientation of the objects precisely. Object recognition and pose detection have great importance in robotics since it helps robots to localize objects. This capability enables industrial robots to autonomously accomplish manipulation tasks such as drilling, pick and placement and part assembly [1]. In image processing, the input is usually an image and the output is either another mapped image or extracted features parameters related to the image. There are various methods for object detection. An object detection system finds objects in the captured image. Object detection system determined the presence or absence of objects in arbitrary scenes and invariant to object scaling and orientation, camera viewpoint and changes in the environment [2].

Due to the large volume of images, the processing time for decision making is greatly increased, while not all parts of the image contain editing information. One useful way to reduce image processing time in online scenarios is to reduce the image size. The speed and precision of the robot arm are strongly influenced by the images of the robot's work environment. The smaller the size of the image while retaining the critical information, makes the decision-making process faster. Section 1.1. reports on the approaches in this field. Papers contributions are described in Section 1.2. While, Section 1.3 compares the proposed work to state-of-the-art methods.

1.1. Review of Previous Work

Wavelet transform is widely used in machine vision as an image processing technique for object detection and classification. Wavelet transformation consists of many types such as Haar, Morlet, and Daubechies. Haar is the first type of Discrete Wavelet Transform which was invented by Hungarian mathematical Alfred Haar. For an input represented by list of 2n numbers, the Haar wavelet transform may be considered to pair up input values, storing the difference and passing the sum. The discrete wavelet transform, a generalization of Fourier analysis, is widely used in several signal and image processing applications [3]. Wavelets have been applied in the past to analyze images and are used in many applications in remote sensing, such as removing speckle noise from radar images, merging high spectral resolution images with high spatial resolution images, and texture analysis and classification [4].

Discrete transforms are an efficient way for compressing images. Image compression using those transforms helps substantially with file size and bandwidth usage reduction when we can afford losing precision to some extent [5]. Wavelets transform helps us to obtain multi-scale variance estimates of the signal or measure the multi-scale correlation between two signals. Using reconstruct signal (1D) and image (2D) approximations retain only desired features, and compare the distribution of energy in signals across frequency bands [6]. Template matching is a common computer vision challenge where an algorithm is trying to find similarities between two or more different images [7]. During offline training, an object's template images are sampled from varying viewpoints. During online testing, templates are compared to a scene image by computing the similarity. The object is detected if a template is matched. The object's pose is determined based on the template's training pose [3].

Template matching has been used for a long time in machine vision, and now has been widely accepted in industry [8]. It has proven to perform well in retrieving the pose of an already-identified object. However, it comes with a number of known flaws. For instance, the matching speed is dependent on the number of templates which the method is trying to match. Furthermore, the final decision is about whether an object has been well detected or located, based on a threshold on the matching score [9]. The final approach explored is an image compression System called a Hybrid Wavelet-Based Compression System (HWCS), which is based on the assumption that viewers are more interested in the subject of interest (SOI) for a given image than the background [10].

Vimala proposed a new method, hybrid technique that combines wavelet and neural networking methods [11] which were performed and validated using different standard images and extant denoising methods. These images were degraded using a variety of noise levels to simulate actual noise degradation. Based on the research background, a new approach to reduce the size and noise of images was provided, while retaining the essential information contained in the images for feature extraction, which is relatively faster and more practical than previous methods.

1.2. Proposed Methodology and State-Of-The-Art Methods

The task in visual surveying is to control the pose of the robot's end-effector, relative to the goal, using visual features extracted from an image of the goal object. Online identifying components via taking a photo and matching them with a database for assembly sequence is required. The speed of operation of the entire set is determined by the sum of the time taken for taking photo, image processing, and identification of the piece, its location and orientation, and ultimately the transfer of these features to the robot for decision. As processing and locating speeds increase, the total time will be reduced, resulting in an increase in the speed of robotic assembly. In this article, the Logitech Pro C922 camera was used for imaging. The double density wavelet filter was used to reduce the size of the images and optimize the features extracted image. Finally, using the neural network, the components were intelligently classified, and the components specification was provided in real time to the robot in order to assist the assemble process. This paper presents a new image compression scheme which uses the double density wavelet transform and neural networks to reduce the image size and extract localization information. The most significant features of this method are:

- Fast online detection and classification.
- Using this method does not require any special lighting, due to the Wavelet filter inherent characteristics.
- Producing image compression standards that give excellent compression performance in terms of compression ratio, peak signal to noise ratio (PSNR) and bits-per-pixel (bpp).
- Reduces computational time and optimizes the accuracy of identifying lines and edges.
- Accurate method for detection of parts location and orientation in robotic Assembly applications.

2 THE PROPOSED METHOD

First, Images of the components involved in the assembly process were captured in different views. Second, the image size was reduced and decomposed using a discrete wavelet transform. Pre-processing is an essential step in image processing in order to speed it up and its size is reduced 4 times. To explore and to understand how the various image features affect the coding performance, grey-scale image histogram features are used to analyze color images. Greyscale image feature analysis is being employed initially as there is limited data on coding performance measures for color images. This will allow certain quantitative and qualitative comparisons to be made. The histogram features are statistically based features and they can provide information about the characteristics of the color distribution of a color image. (These features include first order statistics, for example, mean, standard deviation, variance, energy, entropy, kurtosis, and entropy). Then the number of objects inside each image is extracted and their main characteristics are collected. This methodology is shown in “Fig. 1”.

A template bank is created by collecting data of the template objects and their main features just like that in Table 1. For automated assembly tasks, we need to capture every piece which comes online into the assembly process and extract the main features of it, then recognizing that this piece is a part of the pattern set in the assembly process or not. If the answer is yes, then using a neural network algorithm, the components are matched and classified with available database patterns. At this stage, the position and orientation of the component are calculated in the end-effector coordinate. i.e., the center coordinates of the piece and its orientation are sent to the robot controller pick and placement assignments in the assembly process.

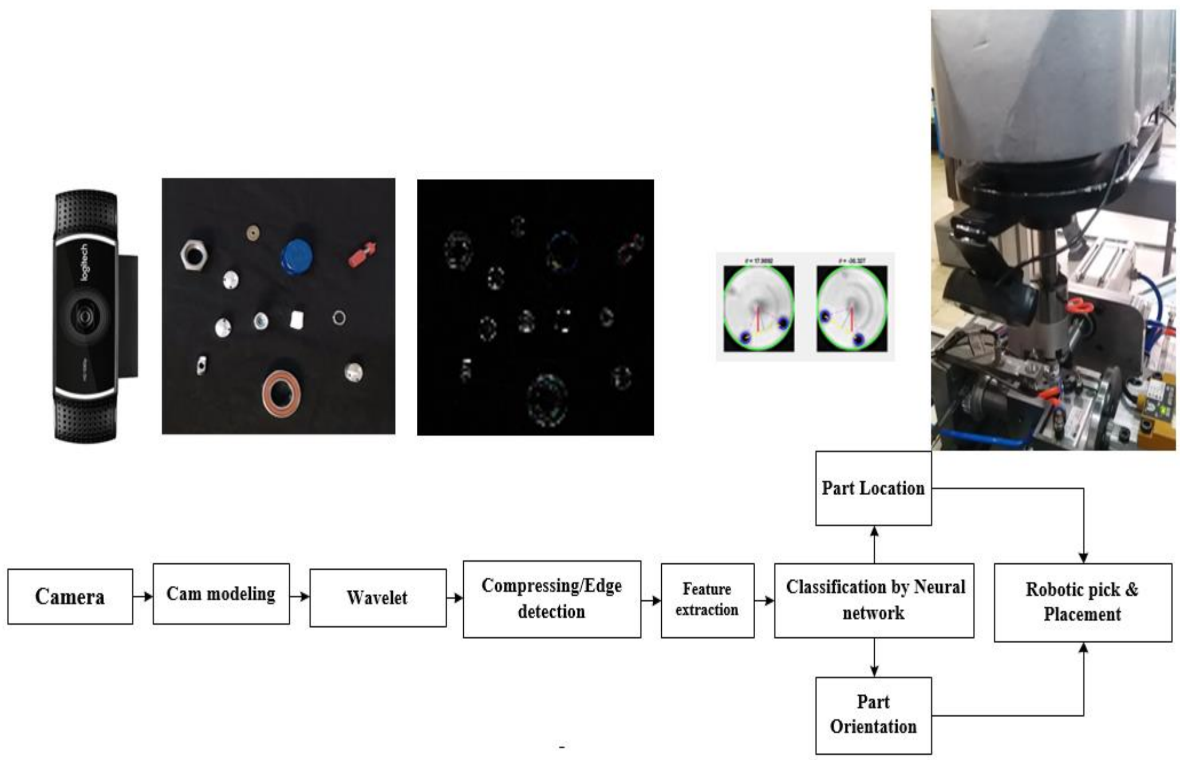

Fig. 1 Block diagram of the proposed method.

2. 1. Required Steps for the Proposed Method

The Proposed Method includes 8 basic steps

- Online Image capturing.
- Noise reduction and compression of the image.
- Decomposition of the image.
- Key features of objects are extracted from a set of reference images which are stored in a database.
- Selection key feature's which can distinguish the objects from each other.
- Objects are recognized by individually comparing each feature with that for in the database.
- Finding best object with matching features using an artificial neural network.
- Sending the location and orientation of the component to the robot for assembly decision.

All steps are basic, but three of them are the utmost importance for the proper extraction of assembly parts. Capturing the right image, noise reduction and image processing in an error-prone factory environment, may be result in extracted features which are far from reality.

2.2. Mathematical Theory

In the digital signal processor, a signal could be written in a discrete sequence. So, the discrete wavelet transform can be useful to process it.

$$\omega_s^i f(n,m) = \iint f(u,v)\psi_s^i(n-u,m-v)dudv \qquad (1)$$

By discretizing equation.

$$\omega_s^i f(n,m) = \sum_{k,l}(m-1-k,n-1-l)\psi_{k,l}^{s,i} \qquad (2)$$

Where in "Eq. (2)":

$$\psi_{k,l}^{s,i} = \iint_{[k,k+1],[l,l+1]}\psi_s^i(u,v)dudv = \int_{\frac{l}{s}}^{k+1/s}\int_{\frac{l}{s}}^{l+1/s}\psi^i(u,v)dudv \qquad (3)$$

Since the number of multiplication operations may come largely in solving "Eq. (3)" so, it maybe time consuming. The equation for a 2D finite impulse response of a filter can be represented similarly in the discrete form which is given by:

$$y_{n_1,n_2} = \sum_{k_1=0}^{l_2-1}\sum_{k_2=0}^{m_2-1} h_{k_1,k_2}x_{(n_1-k_1,n_2-k_2)} \qquad (4)$$

Where, y_{n_1,n_2} and x_{n_1,n_2} $(n_1 = 0,1,\ldots\ , n_2 = 0,1,\ldots)$ stand for the input and output of the filter, respectively and h_{k_1,k_2} denotes the filtering coefficients [2].

$k_1 = (0,1,l_2-1)$, $k_2 = (0,1,m_2-1).\psi_j^p(x_1-2^j n_1)\psi_j^q(x_2-2^j n_2)$

having the same scale along x_1 and x_2. These separable wavelet packet bases are associated to quad-trees, and divide the two-dimensional Fourier plane (ω_1,ω_2) into square regions of varying sizes. Separable wavelet packet bases are extensions of separable wavelet bases. If images are approximated at the scale 2^j , the root of the quad-tree could associate the approximation space $V_L^2 = V_L \otimes V_L \subset L^2R^2$. Decompose V_L with the binary tree of wavelets packets space. $\omega_j^p \subset V_L$ that admits an orthogonal basis $\omega_j^p(t-2^j n)_{n\in z}$ .The two-dimensional wavelet packet quad-tree is composed of separable wavelet packet spaces. Each node of this quad-tree is labeled by a scale 2^j and two integers $0 \le p \le 2^{j-L}$ and $0 \le q \le 2^{j-L}$, and corresponds to a separable space [12]:

$$\omega_j^{p+q} = \omega_j^p \otimes \omega_j^q \qquad (5)$$

The resulting separable wavelet packet $x=(x_1,x_2)$ could be written in the form of:

$$\psi_j^{p+q}(x) = \psi_j^p(x)\psi_j^q(x) \qquad (6)$$

Theorem. 1

Let be a scaling function and be the corresponding wavelet generating a wavelet orthonormal basis. By definition three Wavelets equation as:

$$\begin{aligned}\psi^1(x) = \phi(x_1)\psi(x_2)\psi^2(x) = \\ \psi(x_1)\phi(x_2)\psi^3(x) = \psi(x_1)\psi(x_2)\end{aligned} \qquad (7)$$

And denote for $1 \le k \le 3$:

$$\psi_{j,n}^k(x) = \frac{1}{2j}\psi^k\left(\frac{x_1-2^j n}{2^j},\frac{x_2-2^j n}{2^j}\right) \qquad (8)$$

The wavelet family is an $n \in z^2$ $\psi_{j,n}^1,\psi_{j,n}^2,\psi_{j,n}^3$ orthonormal basis of ψ_j^2 and $\psi_{j,n}^1,\psi_{j,n}^2,\psi_{j,n}^3$ $j,n \in z^3$ is an orthonormal basis of $L^2(R^2)$.

Theorem. 1 proves that an orthogonal basis $\omega_j^{p,q}$ is obtained with a separable product of the wavelet packet bases of ω_j^p and ω_j^q, which could be written as $\psi_j^{p,q}(x-2^j n)_{n\in z^2}$. At the root $\omega_L^{0,0}=V_L^2$, the wavelet packet is a two-dimensional scaling function [13].

$$\phi_L^{0,0}=\phi_L^2=\phi_L(x_1)\phi_L(x_2) \tag{9}$$

The decomposition coefficients of an image in a separable wavelet packet basis are computed with a separable extension of the filter bank algorithm. Let $b[n]$ be an input image with pixels at a distance $2L$. By associating $b[n]$ to a function approximated at the scale $2L$, with decomposition coefficients $a_L[n]=\langle f_x,\phi_L^2(x-2^l n)\rangle$ that are defined $b_n=2^{-L}a_L[n]\approx f(2^L n)$, the wavelet packet coefficients could be written as [13].

$$d_j^{p,q}[n]=\langle f,\psi_j^{p,q}(x-2^j n)\rangle \tag{10}$$

Characterize the orthogonal projection of f in $\omega_j^{p,q}$. At the root, $d_L^{0,0}=a_L$, the wavelet packet is a two-dimensional scaling function derived as the "Eq. (10)".

$$\psi_L^{0,0}=\phi_L^2(x)=\phi_L(x_1)\phi_L(x_2) \tag{11}$$

One-dimensional wavelet packet spaces satisfy:

$$\psi_j^t=\psi_{j+1}^t\oplus\psi_{j+1}^{2t} \quad t=p,q \tag{12}$$

Using "Eq. (9)" in the two-dimensional express that $\omega_j^{p,q}$ is the direct sum of the four orthogonal subspaces:

$$\omega_j^{p,q}=\omega_{j+1}^{2p,2q}\oplus\omega_{j+1}^{2p+1,q}\oplus\omega_{j+1}^{2p,2q+1}\oplus\omega_{j+1}^{2p+1,2q+1} \tag{13}$$

These subspaces are located at the four children nodes in the quad-tree.

Theorem. 2
At the decomposition

$$\begin{aligned} d_{j+1}^{2p}[k]&=d_j^p*\bar{h}[2k]\\ d_{j+1}^{2p+1}[k]&=d_j^p*\bar{g}[2k]\end{aligned} \tag{14}$$

So the decomposition coefficients of an image in a separable wavelet packet basis are computed with a separable extension of the filter bank algorithm, from the separability of wavelet packet bases and the one-dimensional convolution formula of theorem. 2 and the two-dimensional case [13].

$$\begin{aligned} d_{j+1}^{2p,2q}&=d_j^{p,q}*\bar{h}\bar{h}[2n]\\ d_{j+1}^{2p+1,2q}&=d_j^{p,q}*\bar{g}\bar{h}[2n]\\ d_{j+1}^{2p,2q+1}&=d_j^{p,q}*\bar{h}\bar{g}[2n]\\ d_{j+1}^{2p+1,2q+1}&=d_j^{p,q}*\bar{g}\bar{g}[2n]\end{aligned} \tag{15}$$

Thus, the coefficients of a wavelet packet quad-tree are computed by iterating these equations along the quad-tree's branches. A major concern of this research is to identify the best wavelet for compressing still color images, different wavelets were used to compress a selected set of color images. The initial results show that different wavelets produce different varied coding performance. Coding performance refers to Peak Signal-to-Noise Ratio (PSNR), Compression Ratio (CR) and bits-per-pixel (bpp). The calculations are performed with separable convolutions along the rows and columns of the image [14], as illustrated in "Fig. 2".
Image has been decomposed on wavelet decomposition techniques using transform with different levels of decomposition. Since the assembly parts may be placed in different directions, the edge detection and their characteristics could be different by applying the wavelet transform on the image. By converting images to signal in space or time domain, calculate the multi-level wavelet coefficients. The processed wavelet coefficients, need to be transformed inversely to get the desired image. The standard peak signal-to-noise ratio PSNR is defined by [12]:

$$PSNR = 10 * log_{10}(\frac{255^2}{MSE}) \tag{16}$$

And the mean square error (MSE) of Image is defined by [12]:

$$MSE=\frac{1}{MN}\sum_{y=1}^{M}\sum_{x=1}^{N}\left[I(x,y)-\breve{I}(x,y)\right]^2 \tag{17}$$

Where, M and N are the row and column of the image respectively. However, the PSNR of a color image with red, green and blue components is defined by [15]:

$$PSNR = 10*log_{10}\{\frac{255^2}{\frac{MSE\,(red)+\,MSE\,(green)+\,MSE\,(biue)}{3}}\} \tag{18}$$

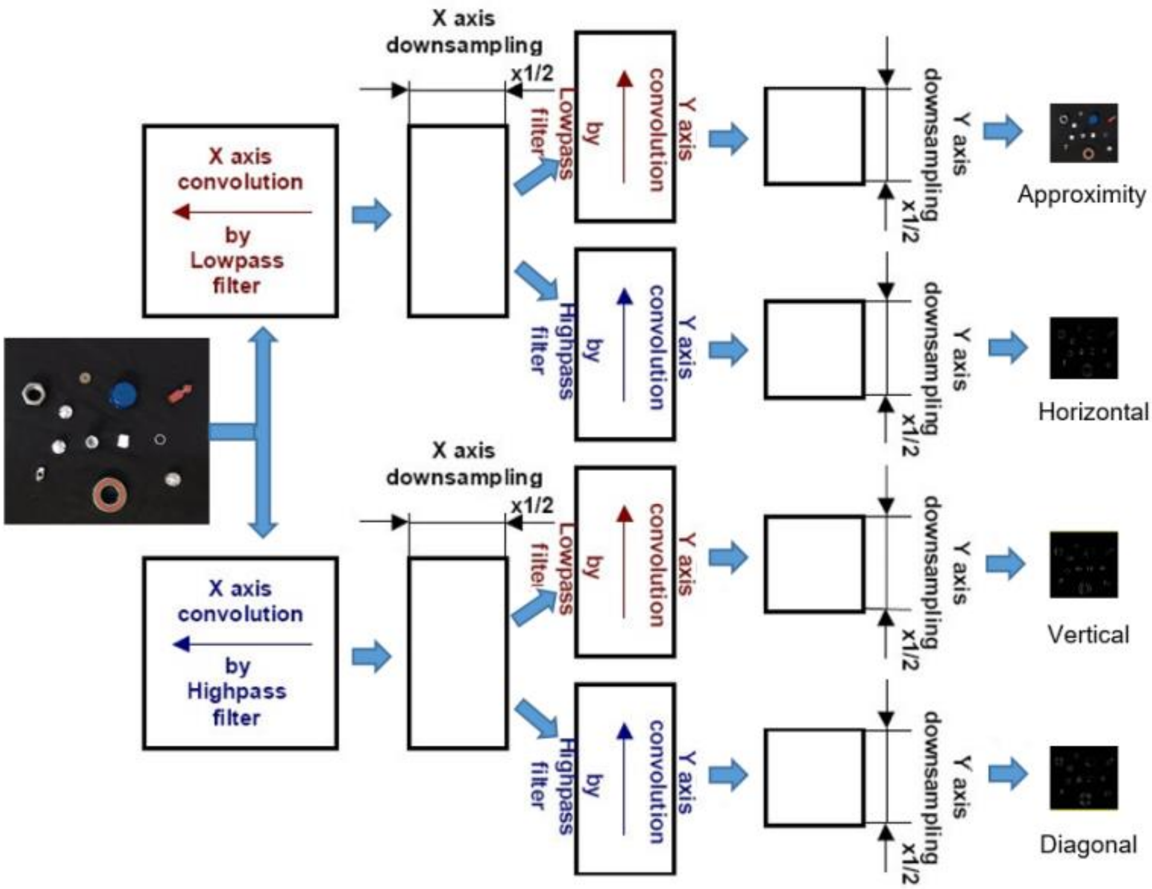

Fig. 2 Double density 2D-DWT packet decomposition.

A high value of PSNR is good because it means that the signal-to-noise ratio is high which means less error in the image. In image compression, the 'signal' is the original image, and the 'noise' is the error in reconstruction. Image compression involves reducing the size of image data, while retaining necessary information. The reduced file is known as the compressed file. Compression ratio is defined by [15]:

$$\text{Compression ratio} = \frac{\text{UnCompressed Image size}}{\text{Compressed Image size}} \tag{19}$$

An alternative way to State the compression is to use the terminology bits-per-pixel, which is defined by [16]:

$$\frac{\text{Bits}}{\text{pixel}} = \frac{\text{no.of.bits}}{\text{no.of.pixels}} = \frac{8\text{*no.of.bits}}{\text{Image size}} \tag{20}$$

2.3. Feature Extraction

Transforming the input data into the set of features is called feature extraction. Feature extraction describes the relevant shape information contained in a pattern so that the task of classifying the pattern is made easy by a formal procedure. Feature extraction is a special form of dimensionality reduction. The main purpose of feature extraction is to obtain the most related information from the main data and expose them into a lower dimension space. Since the location and orientation of the parts can affect the extracted features, it is necessary to fix the camera and captured 30-50 photos of each piece in deferent positions. Figure 3 Shows the sample parts which are used as the database. Applying a wavelet filter to the sample image such as “Fig. 3”, ultimately helps to extract the feature of the image after reducing the image size and finding the edge of the parts in the image.

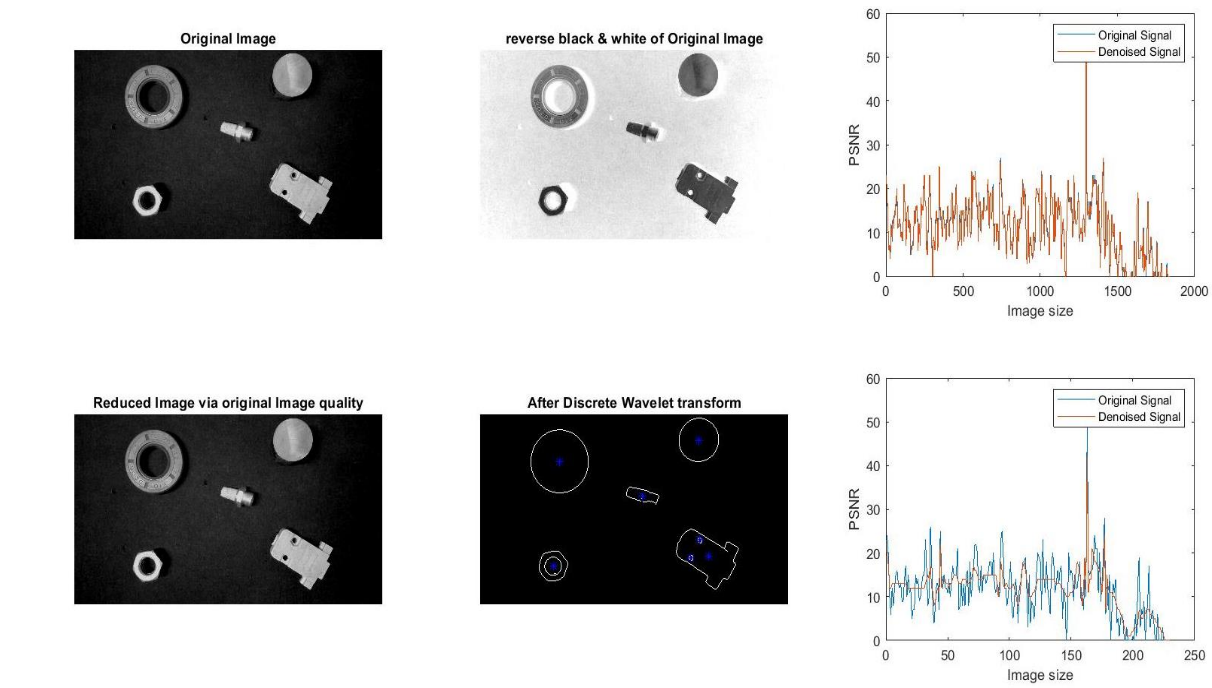

Fig. 3 Effect of wavelet transform on reducing size and removal noise.

The essential features were selected such as Area, Major axis, Miner Axis, Perimeter and orientation, as shown in "Table 1". Choosing these features are helpful to eliminate other info of image which are time-consuming to commutate. Therefore, a detailed choosing of selected features could be helpful in data accuracy.

Table 1 Extraction parts features

part	Area	Major & Minor Axis	perimeter	orient
1	112970	515.36 374.20	1424.08	-54
2	61104	279.79 278.13	874.94	-77.21
3	36725	267.36 263.78	775.29	-29.51
4	76569	576.15 279.45	1921.47	-1.04
5	65395	561.62 198.93	1298.67	11.30

Using the 2D-DWT filter eliminates the noise in the images that cause computational errors and improves the edge resolution of the parts as shown in "Fig. 3". This approach presents for image region classification that combines low-level processing with high-level scene understanding.

For the low-level training, predefined image concepts are statistically modeled using wavelet features extracted directly from image pixels. For classification, features of a given test region compared with these statistical models provide probabilistic evaluations for all possible image concepts. Maximizing these values themselves already leads to a classification result (label) [17]. By collecting image information, in a short time, the system will automatically be able to detect new pieces which are passed in front of the camera and match their features with the information in the database so classify them.

According to "Table 2", the total time required by our proposed edge detector is small and takes just some milliseconds for extract object features. This Table shows a comparison of the time requirement between our proposed method and other methods (Daubechies, Haar , Discrete Cosine Transform (DCT), Hybrid Wavelet-based Compression System (HWCS)) this comparison proves that our proposed method performs well and has less time requirement than others and gives an approximate speed-up 1.3 times.

Table 2 Extraction Time (ms) requirement comparison between our method and others

part	Daubechies	Haar	DCT	HWCS	Propose method
1	93	87	85	70	63
2	56	58	55	74	50
3	78	73	68	61	54
4	80	73	69	63	59
5	91	78	80	70	67

2.4. Classification

A pattern recognition and classification system consists of a feature extractor, a pattern matcher, a reference database and a decision-maker. In the presented work, the MLP neural network is used for pattern matching. The wavelet method contains the neural network training and testing. During the training process, the output of the wavelet acts as the input for the neural network. The wavelet functions are obtained from a mother wavelet function via translation and size expansion [18].

The number of neurons, weight bias, and hidden layers is fixed during the training process. This network has the potential to learn and create a nonlinear network from the Gaussian noisy input pixel. The training process is a scaled conjugate gradient algorithm. The trained data and network structure are stored in the images. The expected error rate and MSE values are given as targets to the network. When the targets are met, the network stops the iteration process, providing a denoised image and performance measured values of MSE and PSNR. The proposed ANN incorporates all of the above DWT techniques, and the ANN-based hybrid denoised techniques are implemented for the images. Validation performance of FFNN with mean squared error is shown in "Fig. 4".

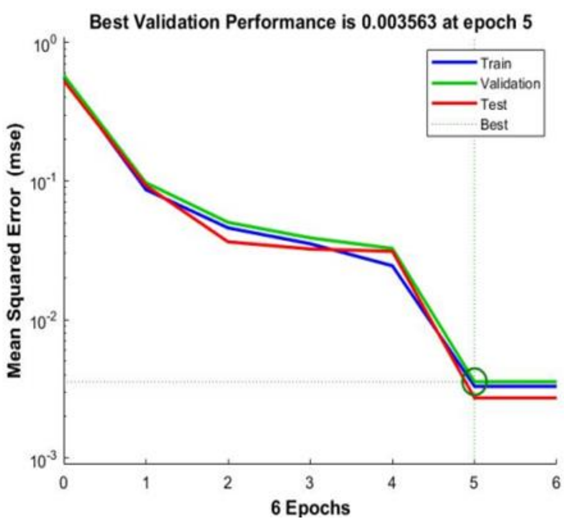

Fig. 4 Validation performance of FFNN with mean squared error.

To classify the parts in the production line, a thousand pieces were photographed in different viewpoints and extracted according to "Table 1". Each image may contain multiple parts, as shown in "Fig. 3", this image contains 5 parts which important features were extracted in accordance to "Table 1" that take 10 images from each object in different situations and filter them by the proposed method, the network input was chosen as a matrix whereof they used as network training and as a validation.

The hidden layers of the neural network were trained according to the process of testing and validation. The performance of HDWNN through the learning operation is about 0.0035 by considering MSE as the performance criterion result which is shown in "Fig. 5". In this research, the components were classified in 280 categories. Every input is assigned to one of the k mutually exclusive classes. A multi-layer perceptron was used to classify the extracted features from the parts. After classifying the parts, the angle of alignment and center coordinate should be sent to the robot controller. Suppose an image of the part on the conveyer-belt, so the robot automatically should be able to find the coordinates of the object in (x, y) plane, their orientation about the x-axis and find the actual size of them.

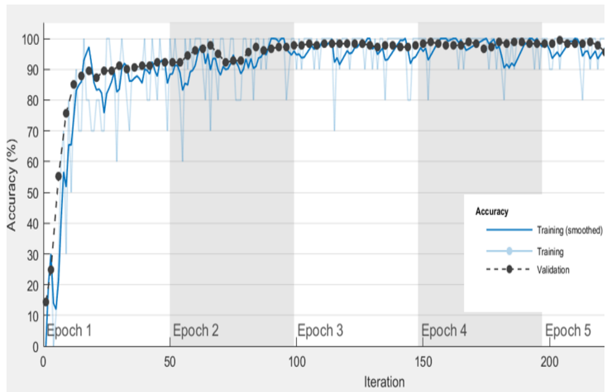

Fig. 5 Accuracy of the Method in object detection and classification.

3 CONCLUSION

The efficiency of automatic operations is heavily influenced by the speed and accuracy of the machine vision system. Large amounts of information increase computing time. Image quality enhancement is an important image processing task, wherein noise reduction and compressing an image is essential for accurate image diagnoses because the presence of noise in an image produces incorrect information. The hybrid technique combines wavelet and neural networking methods which were performed and validated using different standard images and extant noise reduction methods. This paper offers a new method that reduces Image size and diminishes the process times. The proposed method gave a lower MSE and a higher PSNR value for each noise level.

By extracting the main features of the images, parts are categorized and classified. These images were degraded using a variety of noise levels to simulate actual noise degradation and were compressed with the training of the neural network and its evaluation, it was determined that the proposed method could detect and categorize new parts entering the visual machine with an 95% accuracy as shown in "Fig. 5". The proposed hybrid method provided a 58.8% improvement from noisy to denoised image, whereas artificial neural network-based wavelet transform technique provided a 44.13%

improvement. Eventually, the object information (such as Location, Orientation, big diameter, and minor diameter) with respect to the inertial coordinate system are sent to the robot controller for assembly applications.

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