An Adaptive Selection of Filter Parameters: Defect Detection in Steel Image Using Wavelet Reconstruction Method

Sang-Gyu RYU,1,2) Gyogwon KOO3) and Sang Woo KIM3)*

1) School of Electrical Engineering, Korea Advanced Institute of Science and Technology (KAIST), Daejeon, 34141 South Korea.
2) 1st R&D Research Group, Agency for Defense Development, Daejeon, 34186 South Korea.
3) Department of Electrical Engineering, Pohang University of Science and Technology (POSTECH), Pohang, 37673 South Korea.

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We proposed a scheme for adaptively selecting filter parameters for detecting defects in various image textures. To implement the proposed scheme on a target steel image, we used wavelet reconstruction method. The adaptive parameter-selecting scheme was presented by analyzing the textures in an image and obtaining the appropriate parameters from a pretrained neural network by inputting these texture features. Experiments were conducted to detect corner cracks in the images of a steel billet, and the proposed scheme was compared with a conventional wavelet reconstruction method. The experimental results showed that our proposed scheme was effective in detecting defects in various textures of the target images.

KEY WORDS: optimal filter; machine vision; visual inspection; steel defect detection; wavelet reconstruction; texture image processing.

1. Introduction

Vision-based defect-detection systems are currently being applied to many manufacturing processes and have contributed to factory automation and production of high-quality goods through the development of image-analysis techniques. There are many image-analysis techniques used in surface defect detection such as statistical-, filter-, and model-based approaches.1) Among them, filter-based approach is highly advantageous for spatial-frequency analysis, which is more useful on surfaces with noisy and variations in intensity.2) Further, some of these approaches analyze the statistics and structure of a defect after filtering to improve the reliability of the defect-detection process. The general process of a filter-based approach is shown in Fig. 1. First, images are preprocessed, e.g., through segmentation to find regions of interest (ROIs), or undergo a smoothing process to eliminate noises, depending on the particular application. After preprocessing, the images are filtered using the designed filters to enhance the response of the defective regions and minimize the response of normal regions. Finally, the defects are detected after binarization of the filtered images,3–5) or with additional classifications using a machine learning method.6,7)

Many filters have been proposed for filter-based approaches, varying from a fundamental Fourier analysis to recent Gabor filter and wavelet-based approaches. Along with the development of such filters, methods for determining the filter parameters have also been proposed. While the parameters are generally selected empirically, an empirical method includes human intervention, which is crucial for the performance of the filters used.

To reduce human intervention, optimal filters have been proposed. Optimal filter approaches design kernel or filter parameters by comparing the mean and standard deviation values of regions within a filtered image according to a specific criterion. In view of the texture homogeneity of the target image, filter designs can be categorized into one of two types:

1. Filter designs for homogeneously textured images such as textiles, liquid crystal display (LCD) panels, ceramics, and semiconductors.8,9)

2. Filter designs for inhomogeneously textured images such as steel and solar wafers.3,10–14)

For homogeneously textured images, the filters are designed to eliminate repetitive background patterns or textures, and the defects are detected based on the response of the filtered images. In this case, an optimal filter is relatively effective because filters are designed as the response...
of the background is minimized in filtered images, and abnormal patterns such as defects are easily detected. In the early stage of designing an optimal filter, the kernel of the filter is optimized using cost functions such as those by Mahalanobis and Singh (JDS), Unser (J_U), and Fisher (J_F) for texture discrimination.\(^9\) Next, a method to optimize the parameters of a Gabor filter is proposed using \(J_F\) to detect textile flaws.\(^9\) These optimal filter approaches have shown satisfactory results for homogeneous textures.

In inhomogeneously textured images, filter designs are more focused on the characteristics of the defects, such as the structural and spectral characteristics, rather than the backgrounds, because backgrounds may contain some random textures or indescribable patterns. Optimal filter approaches have also been recently applied to inhomogeneously textured targets. Yun optimized the parameters of a Gabor filter using a modified version of \(J_{DS}\) to detect defects in steel.\(^1\) Yun also employed a scheme that optimizes the mother wavelets of a wavelet transform for defect detection,\(^1(2)\) which was initially proposed for texture discrimination.\(^1(5)\)

However, these optimal approaches in inhomogeneously textured targets are less effective than in homogeneously textured targets. Particularly in steel images, textures vary depending on the grade, temperature, state of the steel, among other factors (Fig. 2). Further, the textures in steel images are difficult to categorize, and a filter cannot be designed for each categorized texture or optimized for each steel image because of the computational time in the optimization process.

Recently a complete CNN machine learning architecture has been widely applied in many areas because of its performance and potential in the future. These complete machine learning approaches are also studied for steel defect detection and some results show good performance. However, when the domain knowledge such as the spectral, morphological characteristics and effective features of patterns are known as in defect detection in steel image, a more compact defect detection system can be designed using domain knowledge.

Further, when applying a defect detection system in a steel factory, a highly reliable and explainable system should be applied because a malfunction of it results in tremendous financial loss. Therefore, we need to explain briefly how the defect detection system works, and how this system processes defects. This is not easy for the complete CNN machine learning architecture to explain why some defects are not processed or failed to be detected.

For these reasons, we propose a hybrid filter design scheme for selecting the filter parameters by considering the textures of the images. The proposed scheme is applied to detecting corner cracks on the images of a steel billet. For the implementation, wavelet transform (WT) and wavelet reconstruction (WR) method, which is a wavelet-based filter approach, is used. The filter implemented using the proposed scheme is called suboptimal wavelet reconstruction (SWR) since the filter selects the suboptimal parameters from a neural network (NN) and employs a WR method.

In the next section, a review of wavelet transform (WT) and WR method is presented for a better understanding of the proposed scheme and its implementation. In Section 3, the details of the proposed scheme and its implementation to a WR method are first illustrated, and post-processing of the filtering is then presented since the proposed scheme is compared after post-processing for a practical comparison. The experimental results are then shown in Section 4, and some concluding remarks are given in Section 5.

2. Review of Wavelet Transform and Wavelet Reconstruction Method

A WT is a time-spatial analysis, and because it represents texture features well, wavelet-based approaches have been applied to texture segmentation or retrieval in early applications.\(^1(6,17)\) Some wavelet-based approaches have moved toward defect-detection applications.\(^1(11,12,18,20)\) In this section, a brief illustration of WT and WR method is given.

2.1. Wavelet Transform

A WT decomposes information into approximated and detailed parts. The approximated parts contain low-frequency information, and the detailed parts contain high-frequency information. By continuously decomposing the approximated parts, we can subdivide and analyze low-frequency information more closely. Both the approximated and detailed parts are obtained using wavelet coefficients \(d_{j,k}\):

\[
\psi_{j,k}(t) = 2^{-j/2} \psi(2^{-j} t - k) \quad \cdots \quad (1)
\]

\[
x(t) = \langle a_{j,k}, \psi_{j,k}(t) \rangle = \sum_{j,k} a_{j,k} \cdot \psi_{j,k}(t) \quad \cdots \quad (2)
\]

\[
a_{j,k} = \langle x(t), \psi_{j,k}(t) \rangle = \int x(t) \cdot \psi_{j,k}(t) dt \quad \cdots \quad (3)
\]

where \(\psi(t)\) is a kernel function, \(j\) is the dilation, \(k\) is a translation, and \(x(t)\) is the original signal.

A 2D WT can be employed by simply performing a 1D WT in two dimensions, \(x\) and \(y\) (Fig. 3). The 2D WT divides a 2D signal into four bands: horizontal, vertical, diagonal and approximated band. The scaled and translated wavelet functions of each band can be obtained through Eq. (4).

\[
\phi_{i,m,n}(x,y) = 2^{j/2} \phi(2^i x-m, 2^j y-n),
\psi_{i,m,n}(x,y) = 2^{j/2} \psi(2^i x-m, 2^j y-n) \quad \cdots \quad (4)
\]

where \(i = \{H,V,D\}\).

In a 2D WT, scaling function \(\phi(x,y)\), horizontal wavelet \(\psi_h(x,y)\), vertical wavelet \(\psi_v(x,y)\), and diagonal wavelet \(\psi_d(x,y)\) are calculated as follows:

![Fig. 2. Images of billet product: various textures caused by different grade, temperature and process of billet.](image-url)
2.1. Wavelet Reconstruction Method

Some wavelet-based defect-detection methods selectively analyze specific bands of the decomposed images by considering mean energy of each band. A WR method is similar to these wavelet-based methods, but it suppresses unwanted bands and enhances the desired bands by multiplying the reconstruction weights to each decomposed image after a WT (Fig. 4). Bands that contain a lot of background information are multiplied with a low-value reconstruction weight and bands that contain a lot of defect information are multiplied with a high-value reconstruction weight. By inverse wavelet transforming images in which the weights are multiplied, background patterns or textures are suppressed, and defects are more recognizable in the reconstructed image.

A WR method is widely applied to many defect-detection systems,\(^{22}\) however, this type of WR approach requires a careful selection of the reconstruction weights.\(^{20}\) When reconstruction weights are inappropriately selected, the performance of the defect detection becomes unreliable. To eliminate human intervention in selecting the reconstruction weights, an algorithm that selects a wavelet band automatically by considering the energy ratio of each decomposed band is proposed.\(^{23}\) However, this method also includes human intervention in choosing a threshold value and it is a binary selection of specific bands. Instead, selecting the appropriate weights through an optimization process will be more effective. By implementing the proposed scheme in a WR method, the reconstruction weights can be selected adaptively to each input image, which more effectively facilitates the defect detection.

3. Proposed Scheme and its Implementation

In this section, the details of the proposed filtering scheme are introduced, and the implementation of the proposed scheme in a conventional WR method, called SWR, is illustrated. The implemented SWR is designed for the detection of corner cracks in a steel billet (Fig. 5).

In addition, post filtering processes are illustrated because the SWR is compared with a conventional WR method after applying the post-processes. Post-processes include the binarization of a filtered image, defining the defect candidates, and SVM classification to determine whether defect candidates are true defects or if they developed from random textures.

3.1. Proposed Filtering Scheme

As mentioned previously, images of steel products from the same process differ because the quality and temperature of the steel are not always the same. This results in varying steel image textures and makes it difficult to design filters for specific textures of steel image.\(^{24}\) Even worse, scales, which are ferrous oxide, may exist on the surface of a billet, and thus it is difficult to detect corner cracks with a low false-positive rate. For these reasons, the filter parameters are designed by focusing on the characteristics of the defects and average background textures.\(^{11,12}\)

We therefore proposed a scheme for selecting the appropriate filter parameters by considering the textures or patterns of each image (Fig. 6). The main concept of the proposed scheme is that it selects the suboptimal parameters of a filter from a pretrained NN by analyzing the textures of the input image. By implementing the proposed scheme for a specific filter, the parameters of the filter change adaptively to each input image, and the performance of the filter is thereby improved.

Using the proposed scheme, NNs predict suboptimal parameters of a filter from the texture features. Before filtering, the NN should be trained according to the training phase (Fig. 6(a)). In training an NN, the texture features and optimal filter parameters are needed as the inputs and outputs, respectively. These processes are illustrated in the next subsection.

3.2. Implementation of Proposed Scheme

The proposed scheme is first implemented using a single Gabor filter, which was designed.\(^{11}\) We optimized the parameters of the Gabor filter using three cost functions \((J_{IS}, J_{J}, \text{ and } J_{F})\), and obtained the optimal parameters for each function. Optimization results show that a single Gabor filter is not suitable for defect detection in a billet image (Fig. 7), because a single Gabor filter is designed to respond for specific orientation and scale. Therefore, multi Gabor filter, which is a filter-bank approach, is needed. However, a problem remains in that we need to calculate the appropriate
number of filters of the filter-bank. Moreover, even when the filters in a filter-bank are properly optimized, the filters are not mutually orthogonal, which may result in a significant correlation among the texture features. For these reasons, we employed a WR method in our application.

The WR method is a filter-bank approach based on a WT. In this sense, there have been many applications applied, especially for defect detection. The WR method decompose the steel image with orthogonal bases over different scales and shifts. It can discriminate background and defects with various sizes and complex texture characteristics such as corner crack defects. For this reason, we employed a WR method as a filter, and the reconstruction weights of the WR method were selected adaptively using the proposed scheme.

Again, the scheme implemented in our application is called SWR because it selects the suboptimal parameters of a WR method by inputting the texture features of an input image into NNs. After selecting the appropriate weights, which have suboptimal values, the images are reconstructed using a WR method along with the weights.

To design the SWR, we first define the set of defective images for calculating optimal reconstruction weights and texture features. With the set of images, optimal reconstruction weights for each image are calculated, and texture features are extracted from these images. After preparing pairs of optimal reconstruction weights and texture features, the NNs are trained using the optimal reconstruction weights as inputs and the texture features as outputs. The details of the optimization, feature extraction, and training processes are presented in the following subsections.

3.2.1. Optimization

Before optimizing the reconstruction weights based on
specific criteria, the defective regions in the images should be defined to compare the energy between the defective and non-defective regions. We defined the defective regions manually by setting a rectangular window containing defects (Fig. 5), and the rest are non-defective regions. After defining the defective regions, optimal reconstruction weights are computed using Mahalanobis and Singh’s, Unser’s, and Fisher’s cost functions according to Eqs. (8)–(10).

\[
J_{MS} = \frac{\mu_D}{\mu_N}, \quad \text{................................(8)}
\]

\[
J_U = \frac{(\mu_N - \mu_D)^2}{\mu_N \mu_D}, \quad \text{................................(9)}
\]

\[
J_F = \frac{(\mu_N - \mu_D)^2}{\sigma_N^2 + \sigma_D^2}, \quad \text{................................(10)}
\]

where \(\mu\) is the mean, \(\sigma\) is the standard deviation, subscript \(D\) represents a defective region, and \(N\) represents a non-defective region.

For the optimization, we used particle swarm optimization (PSO), which was initially introduced to solve complex nonlinear optimization problems. PSO is known to perform well in optimizing multiple local optimum, and because its performance does not deteriorate severely with the growth of the search-space dimensions, it has therefore been applied to many engineering designs. Ours is a nonlinear, unknown local optimum and multiple search-space problems; therefore, PSO is a suitable approach.

To optimize the coefficients with the cost function \(J_{MS}\) for an image as an example, many sets of independent arbitrary WR filter coefficients are selected by PSO method. After that, the image is filtered with each set of coefficients individually and each cost value is computed by \(J_{MS}\): the mean value of defective regions divided by the mean value of non-defective regions from the filtered image with each set of coefficients. The coefficients which have the largest cost value are the optimal coefficients among them. PSO repeats these processes and stops the iteration when certain conditions are met and the optimized filter coefficients are determined.

In discriminating textures with the optimal filters, \(J_F\) discriminates two textures well because it considers the standard deviation of each region. In our defect detection, however, \(J_F\) provides poor results owing to the calculation of the standard deviation in the denominator. The cost value with \(J_F\) is very high when the standard deviation values are small, and optimal weights are determined as the standard deviation values of each region are very low. Consequently, this results in a reconstructed image showing nothing, in which almost every reconstruction weights approach zero. This is therefore not an effective cost function for an optimal filter for defect detection. The numerical comparison among three cost functions is shown in Section 4.

3.2.2. Feature Extraction

An SWR filter selects the reconstruction weights by inputting the texture features into the NN, and it is therefore very important to extract the appropriate features that represent the textures of an image well. We used six statistical features from an original image and energy features from the decomposed images.

The six statistical features are calculated based on the original image, i.e., the mean, standard deviation, skewness, smoothness, uniformity, and entropy as in Eqs. (11)–(14).

\[
\text{skew} = \sum_{i=0}^{L-1} (x_i - \mu)^3 p(x_i), \quad \text{.................(11)}
\]

\[
S = 1 - \frac{1}{1 + \sigma}, \quad \text{.....................(12)}
\]

\[
U = \sum_{i=0}^{L-1} p^2(x_i), \quad \text{........................(13)}
\]

\[
e = -\sum_{i=0}^{L-1} p(x_i) \log_2 p(x_i), \quad \text{..................(14)}
\]

where \(p(x)\) is a histogram of \(x\) normalized by its length, and \(x\) indicates the pixel values of original image \(I(x,y)\).

To consider the energy features, an image is decomposed
to level-5, and the ratios are calculated by comparing the mean energy of each decomposed image. In total, 15 energy features are calculated: three ratio values of horizontal, vertical, and diagonal images of 5 different levels, while the approximated image is excepted to represent background region and discarded. Energy ratio is the ratio of the average value of a decomposed image over the sum of all the average values. It is calculated using the average value of each decomposed image pixels as in Eqs. (15) and (16).

$$\alpha_{ij}^d = \frac{1}{n_{ij}^d} \sum_{m,n} W_{ij}^d (j,m,n)^2$$  \hspace{1cm} (15)

$$\text{Energy Ratio}(d,l) = \frac{\alpha_{ij}^d}{\sum_{i,j} \alpha_{ij}^d}$$  \hspace{1cm} (16)

where $i$ represents direction (H, V, D), $j$ represents the decomposition level, $n_{ij}^d$ represents the number of pixels in decomposed image of the $i$ direction and $j$-th level, $d$ and $l$ represent specific direction and level of wavelet decomposition, respectively.

When calculating the energy ratio features, the image is decomposed using a wavelet transform, which appears to require a large computational cost. However, images are decomposed when using the WR method, and the energy ratios are calculated simply by squaring the decomposed images, averaging the values of these images, and comparing the average values.

### 3.2.3. Training of Neural Network

Since the texture features of the image and the reconstruction weights have a nonlinear relation, intelligent systems are good candidates for weight prediction. An NN is constructed using one input layer, two hidden layers, and one output layer with a feed-forward connection (Fig. 8).

As an activation function, a sigmoid function is used for each neuron except for neurons of the output layer. For the neurons of the output layer, a pure-linear activation function is used because an NN is used as a predictor. Since we use a linear activation function, some weights are predicted as having values of over 1 or lower than zero, and we trimmed these weights. In training NN, the extracted feature vectors are given as input, and optimal reconstruction weights are given as output. We left out an obvious reconstruction weight to reduce the computational cost; the weight for an approximated image of the last level is set to zero because this level contains very low-frequency information which is mostly background. Consequently, 15 output vectors are selected using NNs with 21 texture features.

One unique aspect is that we predicted only a single weight with an NN because the optimal reconstruction weights have no or less correlation with each other, and it degrades the performance of an NN when the weights are trained simultaneously. We therefore constructed 15 NNs to predict 15 reconstruction weights.

### 3.2.4. Suboptimal Wavelet Reconstruction

Using the trained NN, the reconstruction weights of an image can be obtained by simply analyzing the texture features of the image and inputting the feature vectors into the NN.

Using the selected reconstruction weights, the images are filtered through the same process as used in the WR method.

The selected reconstruction weights are suboptimal values for each input image because they are predicted using NNs, which are trained based on the optimal weights. For this reason, the implemented SWR is superior to a conventional WR which is shown in the experimental results (Section 4.4).

### 3.3. Post-processing

When comparing the proposed SWR with a conventional WR method, it is not practical to compare only cost values or energy of filtered image.\(^{9,12}\) We therefore compared the SWR with the conventional WR after applying post-processing that are generally used for detection of defects in steel images.\(^{8,11,13}\)

A filtered image is generally binarized to find defect candidates since defects appear to have a high response after filtering. However, defect candidates contain many pseudo-defects from the response of random textures because steel images are very noisy. For better detection accuracy, defect candidates are classified through a machine learning method using structural or statistical features from regions of defect candidates. Each process is illustrated in this subsection.

#### 3.3.1. Binarization

Filtered image is binarized to find defect candidates which may possibly be defective regions. For binarization, classical methods such as Otsu’s algorithm result in poor robustness\(^{20}\) owing to the nonuniform surface of a steel image. Instead, a double-threshold method is employed,\(^{39}\) which uses two threshold value. Using the double-threshold method, the shape of a defect is preserved with a low threshold value, $T_{\text{low}}$, and noises are eliminated with a high threshold value, $T_{\text{high}}$.

In the double-threshold method, a binary image calculated with $T_{\text{low}}$ (Fig. 9(b)), and a set of adjacent pixels is defined as a blob. The resulting image from the double-threshold method is obtained by simply removing blobs that do not have higher pixel values than $T_{\text{high}}$. Figure 9(c) shows images with higher pixel values than $T_{\text{high}}$, and binarization result shows blobs in Fig. 9(b) that do not appear in Fig. 9(c) are eliminated.

The threshold value is generally determined by considering the mean and standard deviation of the image as in Eq. (17). Similarly, $T_{\text{high}}$ and $T_{\text{low}}$ are determined adaptively by setting high and low values of $k$. The binarization results

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<table>
<thead>
<tr>
<th>Input layer</th>
<th>Hidden layer 1</th>
<th>Hidden layer 2</th>
<th>Output layer</th>
</tr>
</thead>
<tbody>
<tr>
<td>(22)</td>
<td>(10)</td>
<td>(100)</td>
<td>(1)</td>
</tr>
</tbody>
</table>

Fig. 8. Structure of a neural network for one output: 15 neural networks are constructed for 15 reconstruction weights.
vary as the value of \( k \) changes (Fig. 10), and the final detection performances are largely affected by the binarization. In the experiment, we tested various values of \( k \) for a fair comparison.

\[
T = \mu + k \cdot \sigma, \quad \text{.................. (17)}
\]

where \( \mu \) is the mean, and \( \sigma \) is the standard deviation of an image.

3.3.2. Classification

For classification, a support vector machine (SVM) is used with a radial basis function (RBF). SVM is based on a minimization of structural risk;\(^{30}\) this provides better generalization abilities compared to classical learning approaches, which follow an empirical risk minimization.\(^{31}\) The performance of an SVM in terms of generalization is therefore superior to a conventional learning method, and is also effective in classification of steel image.

After binarization, existing blobs are defined as defect candidates to classify whether they are true defects or whether they occur from random textures. For classification, the features of the defect candidates, including the statistical and structural features, are extracted. The statistical features are shown in Eqs. (11)–(14), where \( p(x) \) is a histogram calculated from the pixels of the original image. The structural features are the perimeters, solidity, compactness, width, and height of a candidate blob. Solidity represents the defect is a convex shape or not and compactness represents the defect is a round shape or not. These features are computed as in Eqs. (18) and (19).

\[
\text{Solidity} = \frac{\text{Area}_{\text{Defect}}}{\text{Area}_{\text{ConvexHull}}}, \quad \text{.................. (18)}
\]

\[
\text{Compactness} = \frac{4\pi \cdot \text{Area}_{\text{Defect}}}{\text{Perimeter}_{\text{Defect}}}^{2}, \quad \text{.................. (19)}
\]

4. Experiments and Results

In Section 4.1, image acquisition system is introduced. With the acquired images, the experimental results of the proposed SWR are compared with those of a conventional WR method with fixed parameters after classification. Before comparing the SWR, there are two considerations for a better SWR design: selecting the appropriate wavelet filter, and selecting the best among three different cost functions. These two considerations are first discussed in Sections 4.2 and 4.3. Next, in Section 4.4, the filtering results are shown and the proposed SWR is compared with a conventional WR.

4.1. Image Acquisition System

To detect defects, there are various image acquisition systems such as 2D and 3D\(^{32,33}\) image acquisition system. In this paper, we focus on the 2D image acquisition system, which is cost-effective defect detection system. Our algorithm was tested on a corner billet image which is semi-finished steel products square cross-section, with a size 130 mm x 130 mm and 10 m long. To acquire corner images and detect defects, the system is configured as Fig. 11. Four cameras are installed perpendicular to the moving direction.
of the billets. Cameras are oriented in the 45º direction to the surface of billet, so the corners of billets are on the center of the acquired images. Corner images are transferred to the image processor and our algorithm is applied to detect corner cracks in image. After detecting corner crack defects, information of defects such as locations and size are saved to the server and the system corrects the corner cracks to make a better quality of billets.

4.2. Wavelet Filter Selection

In the selection of an appropriate wavelet filter for our application, we tested seven of the most widely used wavelet filters: Haar, Daubechies 4 (Db4), Daubechies 12 (Db12), Symlets 8 (Sym8), Symlets 20 (Sym20), Bior-orthogonal 2.2 (Bior2.2), and Biororthogonal 3.9 (Bior3.9). Among these seven wavelet filters, the most appropriate wavelet filter is selected by comparing the average of the highest cost values.

The cost value of a specific wavelet filter is the calculated value of a cost function after WR with the wavelet filter. The highest cost value is obtained when the reconstruction weights are optimized according to the cost function. The highest cost values are computed from an image set for each wavelet filter and cost function. With a set of images, the highest cost values are generated as many as the number of images with a wavelet filter and cost function. The highest cost values of each wavelet filter and cost function are averaged over a set of images to make the average cost value. The pseudo-code for calculating average cost value is described in Fig. 12.

The average cost values are normalized to between 0 and 1 by linear transform for simple comparison. The largest value from the same cost function is mapped to 1, and the lowest is mapped to 0 (Fig. 13). At each cost function, a wavelet filter with a higher average cost value indicates that the reconstruction weights are better optimized with the wavelet filter than those optimized with other wavelet filters. Among the seven wavelet filters used, the cost value from the Bior2.2 wavelet filter is the highest for all cost functions, and the SWR is processed using the Bior2.2 wavelet filter in a later experiment.

4.3. Cost Function Selection

In the selection of the cost function, three cost functions $J_{MS}$, $J_J$, and $J_F$ are compared. When comparing the three cost functions, it is impractical to compare the cost value of the optimization results with each cost function. Instead, the hit rate, which indicates the detection accuracy after binarization, is considered. For example, a 90% hit rate means 90%
of the defects are contained in the defect candidates after binarization. The hit rates of the three cost functions are calculated using various values of \( k_{\text{high}} \) and \( k_{\text{low}} \) (Section 3.3.1).

The comparison results (Fig. 14) show that \( J_F \), the best cost function for texture separation,\(^{26}\) is the worst cost function for defect detection. It is because \( J_F \) calculates the standard deviation of defective region, and the cost value is high when the standard deviation of defective region is very small. It results in low response in defective region and a low hit rate. On the other hand, \( J_U \) and \( J_{MS} \) cost functions are not affected by the standard deviation of a certain region, and the SWR using these cost functions performs better than \( J_U \). Based on the comparison results, \( J_{MS} \) is selected because it is simpler to calculate than \( J_U \), and shows a better performance in terms of hit rate than \( J_U \).

![Fig. 15. Filtered results of conventional wavelet reconstruction and proposed suboptimal wavelet reconstruction: (a) original image; (b) energy image filtered using conventional wavelet reconstruction; (c) energy image filtered using proposed suboptimal wavelet reconstruction; (d, g) sub-images of (a); (e, h) sub-images of (b); and (f, i) sub-images of (c).](image)

![Fig. 16. Filtered results of conventional WR and the proposed SWR ((d,g) are defective regions and (j) is non-defective region); (a) original image; (b) energy image filtered with conventional WR; (c) energy image filtered with the proposed SWR; (d, g, j) sub-image of image (a); (e, h, k) sub-image of (b); (f, i, l) sub-image of (c).](image)
4.4. Experimental Results

The proposed SWR was designed using a Bior2.2 wavelet filter and $J_{MS}$ cost function, and this method was compared with a conventional WR with fixed reconstruction weights used. We tested 953 defective images and 5,768 non-defective images for experiments. In Fig. 15, the shape of the corner crack is more distinctive in the SWR-filtered image (Figs. 15(e), 15(h)), and WR-filtered image shows a relatively poor response (Figs. 15(f), 15(i)). In Fig. 16, the response of the non-defective region (Figs. 16(k), 16(l)) is low in both the SWR- and WR-filtered images. However, the response of the defective regions is more distinctive in the SWR-filtered image than in the WR-filtered one. These results show that the proposed SWR can binarize defects with a relatively high-threshold value, which results in a low false detection rate. For practicality, the proposed SWR and conventional WR are compared after classification.

For classification, defect candidates from half of the test images are used for training of SVM and defect candidates from the rest half images are used for calculating detection rate. In classifying defect candidates, the appropriate binarization is very important in determining whether a defect candidate is a true defect or a false response. An appropriate binarization means that a defect candidate blob includes appropriate regions of defect well, and thus the classifier can discriminate a true defect and false response using the shape of the blob and texture features of the defective region. Too small a threshold value results in unnecessary regions being included in a defect candidate blob. On the other hand, too large a threshold value results in necessary regions not being included in a candidate blob, or a blob not appearing.

To compare the performances of the proposed SWR for various values of $k$, true-positive and false-positive rates are measured using different $k$ values in binarization. The experimental results show that the true-positive rate is decreased when too small or too large a threshold value is selected. The experimental results also show that the proposed SWR filter is superior to a conventional filter in both the true-positive and false-positive rates in all values of $k$ (Fig. 17).

5. Conclusion

A filtering scheme that selects the suboptimal parameters of a filter by considering the textures of an image is proposed. In this scheme, the suboptimal filter parameters are obtained through a pretrained NN using the texture features of the target image. Before training the NN, the set of images is defined. With the images set, the optimal parameters of each image are calculated with a specific cost function, and the texture features of each image are extracted. Then, the NN is trained using the pairs of optimal filter parameters and texture features. Finally, the suboptimal filter parameters for a new image can be obtained by inputting the texture features of the image.

To verify its performance, the proposed scheme was implemented to a WR method, and the implemented method is called SWR. The proposed SWR was applied to the defect detection of a steel billet and compared with a conventional WR method. Before implementing the proposed scheme to the WR method, experiments were carried out to find the appropriate wavelet filter and cost function. In selecting an appropriate wavelet filter, the cost values, which were calculated from the optimization results using each wavelet filter, were compared. A higher cost value means that the parameters are better optimized for the wavelet filter, and we selected the Bior2.2 wavelet filter, which showed the highest cost value for all cost functions. In selecting the appropriate cost function, the hit rates of the defects were compared for each cost function. $J_{MS}$ and $J_{U}$ cost functions performed better than $J_{F}$ cost function. Between the formal two, $J_{MS}$ was used since it is simpler to calculate than $J_{U}$.

In implementing the proposed scheme, 15 reconstruction weights of the WR method were optimized using PSO with a Bior2.2 wavelet filter and $J_{MS}$ cost function for billet images. In total, 21 texture features were extracted from the billet images. NNs were trained using the texture features as the inputs and optimized reconstruction weights as the outputs. For SWR filtering, a pretrained NNs selected the suboptimal reconstruction weights by inputting the extracted
texture features of an image. Finally, the images were filtered through the same process as used in the WR method with suboptimal reconstruction weights.

The SWR is compared with a conventional WR method, in which the reconstruction weights are fixed. The experimental results showed that the proposed SWR can enhance the characteristics of the defects better than the conventional WR method. For a more practical comparison, the true- and false-positive rates were calculated after post-processing. Since binarization results highly affect the performance of classification, the experiments are carried using various threshold values for binarization. For each experiment using various threshold values, the proposed SWR was shown to be superior to the conventional WR method.

Using the proposed scheme, every component such as the optimization method, type of filter employed, cost function, and training algorithm can be substituted with other methods.

In implementing the proposed scheme for other applications, the WR method can be substituted with a Gabor or other types of filter-based methods. Instead of PSO, a genetic algorithm or some other optimization method can be used.

The main contribution of this study is the development of a new filter scheme that can adaptively select suboptimal filter parameters by considering the textures of an image. Finally, the images were filtered through the same process as used in the WR method with suboptimal reconstruction weights.

REFERENCES