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Online surface inspection technology of cold rolled strips

Guifang Wu

*Electronic Information Engineering College, Henan University of Science & Technology
China*

1. Introduction

With enlargement of cold rolled strips' productive scale and enhancement of productive speed, traditional quality detection by human eyes becomes more and more unsuitable for surface detection of cold rolled strips, and multimedia technique such as machine vision become impendent. Recent years, CCD cameras and image processing techniques make online inspection of cold rolled strips possible (Sugimoto, T., 1998). An online surface inspection with CCD cameras and image processing techniques is a newly developed technique to detect surface defects of steels on production lines, and it can release workers from hard work and improve work efficiency.

Last century, many detection technique raised up, for example, in the early 70's, there are many new techniques in Japan such as Laser Scan Surface Defect Inspection System, and it developed continuously and can detect some of inner defects by the 80's. Till 90's, some of Japanese corporation developed a new system which can be used to detect the surface of electric steel. By the time of the end of 90's, camera techniques were used to detect the surface of metal strips, especially in German.

But because of the reason of computer technique, the techniques still stop in some normal work conditional, and the advantages of camera techniques weren't exerted fully, especially in developing countries and districts as China, India, etc. Consequently this newly developed technique becomes a hot subject, and its application problems are more and more concerned by people.

In this chapter, an automatic surface inspection system (Kim, S. M., 2006) of cold rolled strips is introduced. The system is equipped with 12 CCD area scan cameras which are used to capture surface image of strips simultaneously. With special illumination units, defects can be distinguished from backgrounds of images because of different gray levels. Many multimedia image processing algorithms are developed to decide whether there are defects on the images and to locate the defects in the whole strips. At the same time, pattern recognition algorithms are developed to classify the defects. With statistical data of defects, such as numbers, sizes, areas, classes, and so on, surface qualities of strips are evaluated.

2. General design of online surface inspection system

2.1 Requirement of System

When producing cold rolled strips, because of high speed, the surface of strips cannot be easily inspected by human eyes, if there are some defects on the surface, it cannot be found by inspector, and all the defects will be sometimes, many impurities would be embed in it, therefore, the surface condition would become too bad to be recognized. In order to inspect surface quality of hot rolled strips, the online inspection system must meet such performance indexes as followings:

1. Velocity requirement: It can work at the velocity of 5~15 m/s;
2. Detection size requirement: It can detect defects of strips with size of 0.5mm× 0.5 mm;
3. Maximum width requirement: The maximum detection width can meet 2000 mm;
4. Work condition requirement: It can work online under any inner condition;
5. Defect position requirement: It can record exact position of defects;
6. Offline requirement: It can display history process of production, and have many offline function such as offline query, offline analysis and offline statistics;
7. Detection rate requirement: The detection rate of common defects can meet 90%, and about 80% for other defects;
8. Recognition rate requirement: The recognition rate of common defects can meet 85%, and about 80% for other defects;
9. Defect types requirement: It can detect over 10 main defects.

2.2 Chief defect types and their causes

When producing steel plate and strip, there are always such chief defect types as scratch, felt horizontal texture, point felt, feather roll imprint, white spot, roll imprint, Edge folding, rust mark, orange texture, emulsion mark, edge crack, scale, crack, air bubble, and so on. The following will analyze the clauses of these defects detailed.

1. Scratch

Scratch is a straight imprint on the surface of steel plate and strip. It is created by the relative movement between two surfaces of steel plate and strip, or between a hard sharp object and one of surface of steel plate and strip. Commonly, scratch is concave and directional in shape, and it is a bit light in black-white image.

Fig. 1. Scratch image of cold rolled strips

2. Felt horizontal texture

Felt horizontal texture is horizontal wave texture along the edge of steel plate and strip, and it is also called edge pucker or edge folding mark. It is mainly caused by the sudden

deduced thickness of edge before temper rolling and extending not enough at edge when temper rolling, or unfolding not enough in rolling direction .this type defect always appears in cold rolled slight sheet.

Fig. 2. Felt horizontal texture image of cold rolled strips

3. Point felt

Point felt is a felt phenomenon with a shape of point or block on the surface of steel plate and strip. The main cause is that the liquidity and plasticity of material is changed by bad shape or exceeded curl tension or bruise on surface.

Fig. 3. Point felt image of cold rolled strips

4. Feather roll imprint

Feather roll imprint is the same as a feather in shape. It is caused by linear load odds in the rolling process. At the same time, it is also related with raw material. The feather roll imprint appears generally in cold rolled steel sheet, and it is easy to form crack in bad condition.

Fig. 4. Feather roll imprint image of cold rolled strips

5. White spot

White spot is a white similar circular spot block on the sur-face of steel plate and strip, its size is variable, but its border is smooth. It is primarily caused by white foam on the surface of plate and strip which has not been disposed immediately, it affect less on surface quality than surface appearance.

Fig. 5. White spot image of cold rolled strips

6. Roll imprint

Roll imprint is a periodic indentation on the surface of steel plate and strip, and appears more or less in a regular form. It is mainly caused by some hard and sharp foreign bodies or im-purities on work rollers, and every round the roller rolls over, there will leave a same indentation on the surface of steel plate and strip.

Fig. 6. Roll imprint image of cold rolled strips

7. Edge folding

Edge folding is a defect with a folding phenomenon on the edge of steel plate and strip. it is caused by untidy curled edge.

Fig. 7. Edge folding image of cold rolled strips

8. Rust mark

Rust mark is a thin layer of corrosion products on the surface of steel plate and strip. It is caused by high air humidity or small drips on surface under the circumstance of wide temperature fluctuations. If corrosion is very serious, the touch will be obvious, and it will be irregular light spot in image.

Fig. 8. Rust mark image of cold rolled strips

9. Orange texture

Orange texture is a block of irregular rough surface like orange skin and is touchable. It is caused mainly by incompletely removed impurities and greasy dirt on work roller during temper rolling.

Fig. 9. Orange texture image of cold rolled strips

10. Emulsion mark

Emulsion mark is a block of untouchable spot. It is caused by the incompletely washed oiliness of earlier rolling working procedure, it is hard to be removed from surface of steel plate and strip, and it generally presents dark in image.

Fig. 10. Emulsion mark image of cold rolled strips

11. Edge crack

Edge crack is a phenomenon of crack or hole at the edge of steel plate and strip. It is caused by linear load odds or strong local stress when rolling or the capacity for deformation of the material is over exceeded.

Fig. 11. Edge crack image of cold rolled strips

12. Scale

Scale is a lay of oxide covered on the surface of steel plate and strip. It is caused by high temperature and insufficient descaling when rolling. The scale can be removed by pickling, but it is hard to be completely eradicated.

Fig. 12. Scale image of cold rolled strips

13. Crack

Crack is a phenomenon of local break of steel plate and strip. Because of the surface tension odds caused by impurity inside steel plate and strip or surface stress concentration caused by surface sag of material, crack will appear while rolling. Crack is generally directional, and vertical crack is most frequent, in some special cases, star crack is occasional.

Fig. 13. Crack image of cold rolled strips

14. Air bubble

Air bubble is undischarged air inside steel plate and strip. Some air will discharge when rolling and will induce a pit in the surface of steel plate and strip. It is produced in the steel-making process.

Fig. 14. Air bubble image of cold rolled strips

2.3 General system design

In order to content all the requirements of above, a system as Figure 15 is designed. The figure shows a general structure of an online inspection system. The system mainly includes 6 parts, such as detection devices, illumination, parallel computation system, server system, mass memory and console system.

Fig. 15. General structure of an online inspection system

From Figure 15, it can be seen that detection devices are installed in the production line. One set of inspection device consists of several CCD cameras worked together with one illumination unit. Because there are two sides of strips, two sets of inspection devices are designed to meet the requirements, one is for upside inspection, the other is for down side inspection, and both sides of strips must be detected simultaneously. Illumination part is very important and essential to the system because it determines whether defects are visualized in images captured by the cameras. There are 2 illumination modes in this system such as dark illumination mode and bright illumination mode. The former is used to detect 3-dimensional defects, and the latter is used to detect 2-dimensional defects. Figure 16 shows these two different illumination modes, Figure 16 (a) is dark illumination mode, and Figure 16 (b) is bright illumination mode.

Fig. 16. Two different illumination modes

In dark illumination mode, the steel strips will reflect the light of illumination device, and only the reflection light of 3D defects will be acquired by camera, but in bright illumination mode, most of reflection light of 3D defects will not be acquired by camera, the reflection light of 2D defects will enter into the camera and be acquired as object images. All the algorithms of whole system are realized by software method, it brings conveniences not only for system upgrade, but also for less outside hardware touch to reduce trouble rate. The software is mainly consist of 2 parts such as client software and server software, Figure 17 and Figure 18 are client software flow chart and server software flow chart respectively.

Fig. 17. Client software flow chart

Client software can meet data acquisition function of online inspection and online observation, including image acquisition, image pre-process and analysis, defect inspection, defect feature extraction and defect recognition etc, and it does not require human intervention as long as guaranteeing the veracity, high effect and stability of the client software. Server software mainly realizes offline defect data analysis, statistic report making and all the mutual control of the whole system, etc. At the same time, the server software provides visual man-machine interface, worker of quality inspection department can know about the surface quality of current coil and historic coils directly by the interface and it can make various statistic report according to the requirement of customer.

Fig. 18. Server software flow chart

In client software, there are 2 special processes in order realize high speed inspection, they are real-time process and just-in-time process. Real-time process takes charge of some immediate information process, so that the system can meet real-time requirement, and just-in-time process takes charge of other information process when CPU is not in full task, so that the system can settle large amount data problem.

3. Main technologies analysis

3.1 Image frozen techniques

When applies multimedia technologies to detect the defects of cold rolled strips with high speed, how to acquire high precision and clear image is very important, and it is a difficulty of automatic surface inspection system for online application. The image acquisition of moving objects techniques are mainly image frozen technique.

Image frozen techniques are adopted to capture surface images of strips at high speed. Shutters of cameras are set very high as 1/4000 seconds to make images jitter slightly, while the illumination units supply enough luminance intensity and make images captured by cameras clear. All cameras are synchronized to capture images simultaneously. To keep service performance and increase service life, the illumination units are not always in operation. They are synchronized with shutters of cameras to make them only lighten at the exposure of cameras.

3.2 Defects detection techniques of moving strips

As positions and shapes of strips vary continuously during producing, reflection of incident lights is different at different areas of strips. Therefore it leads to different backgrounds in

different images captured by cameras. Moreover, gray levels of background differ everywhere in one image because of uneven illumination and reflection. It is difficult to find out defects from non-uniform and ever-changing backgrounds. However, gray levels of backgrounds are gradually changed, while gray levels between backgrounds and defects are abruptly changed. Effective algorithms of defect detection are developed which consists of 4 steps as followings:

1. Background extracted: In this step, backgrounds are found and separated from original images.
2. Gray level calculation: Differential gray levels of backgrounds and original images are calculated.
3. Thresholds decision: One or more threshold values are decided and applied on differential gray levels to determine whether pixels are in defect areas or backgrounds, and pixels in defect areas are marked as "Suspicious Pixels".
4. ROI (Region of Interest) searching and merging; "Region growing" is used to find out defect areas by merging "Suspicious Pixels", and the defect area are called as "Region of Interest", or ROI.

Fig. 19. Defects detection flow chart

3.3 Feature extraction and optimization techniques

3.3.1 Space-domain feature extraction

According to the defect character of cold rolled strips, we can extract 4 types of space domain features.

1. Geometric shape features

Geometric shape features are basic features of object, and they are used to describe geometric shape such as simple descriptor, shape descriptor and fixed quadrature. Simple

descriptor includes area, border perimeter, region center, etc. Suppose x, y are coordinates of horizon and vertical orientation, R is region area, R_x is aggregate of horizon coordinate, R_y is aggregate of vertical coordinate, $f(x, y)$ is image data, R_d is aggregate of defect point in ROI, R_b is aggregate of border point of ROI, some main geometric shape features can be described as followings:

1) Defect area s . It is used to describe the size of defect region as equation (1).

$$S = \sum_{(x,y) \in R_d} 1 \quad (1)$$

2) Defect perimeter P . It is mean defect contour pixel gross as equation (2).

$$P = \sum_{(x,y) \in R_b} 1 \quad (2)$$

3) Region center (x_c, y_c) . It is calculated by barycentric coordinate as equation (3).

$$\begin{cases} x_c = \frac{1}{S} \sum_{(x,y) \in R_d} x \\ y_c = \frac{1}{S} \sum_{(x,y) \in R_d} y \end{cases} \quad (3)$$

4) Defect compact C . It is calculated by equation (4).

$$C = \frac{\|P\|^2}{4\pi \cdot S} \quad (4)$$

5) Defect quadrature feature. There are total 7 quadrature features, and can be described as equation (5) to equation (11), they are fixed for shift, rotation and scale transform

$$IM_1 = \eta_{20} + \eta_{02} \quad (5)$$

$$IM_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \quad (6)$$

$$IM_3 = (\eta_{30} - 3\eta_{12})^2 + (\eta_{03} - 3\eta_{21})^2 \quad (7)$$

$$IM_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{03} + \eta_{21})^2 \quad (8)$$

$$IM_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12}) \left[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2 \right] \\ + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03}) \left[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2 \right] \quad (9)$$

$$IM_6 = (\eta_{20} - \eta_{02}) \left[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2 \right] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \quad (10)$$

$$\begin{aligned} IM_7 = & (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12}) \left[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2 \right] \\ & + (3\eta_{12} - \eta_{30})(\eta_{21} + \eta_{03}) \left[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2 \right] \end{aligned} \quad (11)$$

There are total 19 geometrical feature parameters extracted.

2. Gray level features

Gray level features are very useful in classification and they depict many essential characters of gray image. They are mostly consisted of average, variance, kurtosis, skewness, enrage and entropy of gray level etc., all these characters can be calculated by gray level histogram. There are total 36 gray level character parameters extracted in the software.

1) Gray level average $\bar{b}$

$$\bar{b} = \sum_{b=0}^{L-1} bP(b) \quad (12)$$

2) Gray level variance v

$$v^2 = \sum_{b=0}^{L-1} (b - \bar{b})^2 P(b) \quad (13)$$

3) Gray level kurtosis H_s

$$H_s = \frac{1}{v^3} \sum_{b=0}^{L-1} (b - \bar{b})^3 P(b) \quad (14)$$

4) Gray level skewness H_k

$$H_k = \frac{1}{v^4} \sum_{b=0}^{L-1} (b - \bar{b})^4 P(b) - 3 \quad (15)$$

5) Gray level enrage H_p

$$H_p = \sum_{b=0}^{L-1} P(b)^2 \quad (16)$$

6) Gray level entropy H_E

$$H_E = - \sum_{b=0}^{L-1} P(b) \log_2 [P(b)] \quad (17)$$

At the same time, there are 3 other gray level features such as max gray level, min graylevel and gray level scope, therefore there are total 9 gray level types.

Now, we can extract up 9 gray levels for background images, defect suspicious pixel images, contrast images and defect images respectively, and can get total 36 gray level features.

3. Projection features

It is always very practical to map high-dimensional data into low-dimensional data in engineering, because low-dimensional data are much easier to analyze than high-dimensional data. Projection features are extracted by mapping two-dimensional image signal to one-dimensional digital wave signal, such as wave features, peak value features, impulse features, margin features, skewness features, kurtosis features, and so on. In Figure 20, a defect in image is projected to X direction, and formed a Gray level - X coordinate. There are total 24 projection features in the software.

Fig. 20. X direction projection of defect in an image

Defect image can project to X axis, Y axis, 45° diagonal and 135° diagonal, they can be described as equation (18) to equation (21).

$$p(0^\circ, t) = \int_{R_d} f(t, y) dy \quad (18)$$

$$p(90^\circ, t) = \int_{R_d} f(x, t) dx \quad (19)$$

$$p(45^\circ, t) = \int_{R_d} f(x, x - \sqrt{2}t) dx \quad (20)$$

$$p(135^\circ, t) = \int_{R_d} f(x, \sqrt{2}t - x) dx \quad (21)$$

According to the 4 types projection, we can get

1) Peak value $\hat{X}$:

$$\hat{X} = \max(|x(t)|) \quad (22)$$

2) Average peak value $\bar{X}_p$:

$$\bar{X}_p = \frac{1}{T} \sum_t |x(t)| \quad (23)$$

3) Mean square root X_{RMS} :

$$X_{\text{RMS}} = \sqrt{\frac{1}{T} \sum_t x^2(t) dt} \quad (24)$$

4) Square root scope X_r :

$$X_r = \left(\frac{1}{T} \sum_t |x(t)|^{1/2} dt^2 \right) \quad (25)$$

Consequently, we define 6 projection features as following:

1) Projection wave features F_B :

$$F_B = \frac{X_{\text{RMS}}}{\bar{X}_p} \quad (26)$$

2) Projection impulse features F_M :

$$F_M = \frac{\hat{X}}{\bar{X}_p} \quad (27)$$

3) Projection peak value features F_F :

$$F_F = \frac{\hat{X}}{X_{\text{RMS}}} \quad (28)$$

4) Projection margin features F_Y :

$$F_Y = \frac{\hat{X}}{X_r} \quad (29)$$

5) Projection skewness features F_S :

$$F_S = \sum_x x^3 p(x) dx \quad (30)$$

6) Projection kurtosis features F_K :

$$F_K = \sum_x x^4 p(x) dx \quad (31)$$

According to 4 direction projection, there are total 24 projection features can be extracted, and can be used to recognize the defects.

4. Textural features

For some special defects, they have obvious textural features, Figure 21 shows an image with obvious textural features.

Fig. 21. Typical defect image with obvious textural features

Textural features can be achieved by gray level co-occurrence matrix with statistics, as in equation (32).

$$P(g_1, g_2) = \frac{\#\left\{\left[(x_1, y_1), (x_2, y_2)\right] \in S \mid f(x_1, y_1) = g_1 \ \& \ f(x_2, y_2) = g_2\right\}}{\#S} \quad (32)$$

According to the gray level co-occurrence matrix, 4 textual features such as second-order moment, entropy, contrast and homogeneity can be achieved.

1) Textural second-order moment W_M :

$$W_M = \sum_{g_1} \sum_{g_2} P^2(g_1, g_2) \quad (33)$$

2) Textural entropy W_E :

$$W_E = - \sum_{g_1} \sum_{g_2} P(g_1, g_2) \log P(g_1, g_2) \quad (34)$$

3) Textural contrast W_C :

$$W_C = \sum_{g_1} \sum_{g_2} |g_1 - g_2| P(g_1, g_2) \quad (35)$$

4) Textural homogeneity W_H :

$$W_H = \sum_{g_1} \sum_{g_2} \frac{P(g_1, g_2)}{k + |g_1 - g_2|} \quad (36)$$

3.3.2 Frequency-domain feature extraction

In order to extract frequency domain feature, all the defect images are given by the size of 64×64 shown as Figure 22.

Fig. 22. Some typical defect images with size of 64×64 , (a) is scratch, (b) is edge folding, (c) is feather imprint, (d) is edge crack, (e) is point felt and (f) is felt horizontal texture.

Applying Fast Fourier Transform (FFT) (Chu, E., 2000) to the images and the spectrum images can be achieved. According to the qualities of Fast Fourier Transform, Fast Fourier Transform can transform images from space-domain to frequency-domain, and concentrated most of energies on the center, it can not only reflect gray features and geometrical features of defect images, but also make fast convolution and object recognition to become very real. Therefore, regarding gray values of spectrum images as feature information of defect images can recognize defects, especially the pixels near the central area of spectrum images. The typical spectrum images of FFT are shown as Figure 23.

Fig. 23. Typical FFT images of Figure 22 with size of 64×64 , (a) is scratch, (b) is edge folding, (c) is feather imprint, (d) is edge crack, (e) is point felt and (f) is felt horizontal texture.

According to the result of FFT, it can be seen that nearly all energies are concentrated on the center area, and at the same time, if make all pixels of FFT image as features, the feature set will be too large and unnecessary, and will affect recognition result to some extent in fact. As a consequence, based on many experiments, the crisscross region shown as Figure 4 is taken as original feature set, and the feature number can be calculated with equation (37).

$$n = 32 \times (a + b) - ab \quad (37)$$

In the paper, parameter a is 4 and parameter b is 4 too. Therefore, the total chosen region includes 240 pixels, and the original feature set includes 240 features. The feature set can reflect local outstanding feature information of frequency-domain.

Fig. 24. Optimized crisscross original Feature set region. There are two parameters, parameter a is region width and parameter b is region height.

After given an original feature set, another two extended features are introduced, one is named Sum of Valid Pixels (SVP), and the other is Repletion Ratio of Centre Region (RRCR). The definition of SVP is the count of all the pixels whose values are larger than a given threshold in the full FFT images, therefore by defining SVP, the region outside the crisscross region is taken into consideration, and the feature reflects global statistic feature information of frequency-domain.

Fig. 25. Definition of Repletion Ratio of Centre Region (RRCR) and parameter m is width of centre square region.

Figure 25 shows the definition of RRCR, and it can be defined as equation (38):

$$\eta_m = N / m^2 \times 100\%, \quad m < 64 \quad (38)$$

N is amount of features whose value are greater than a given threshold value in a $m \times m$ centre region. Parameter m can be given as a needed value. This feature can reflects local statistic feature information of frequency-domain in low frequency section. In the paper, three RRCR features are extracted, they are η_5 , η_{10} and η_{15} .

3.3.3 Feature optimization

Fig. 26. Feature optimization and defect recognition of hot rolled strips

The process of using genetic algorithm (Hannes, L., 2006) to optimize the feature set is a process of setting the parameters of genetic algorithm which can describe problem best. Genetic algorithm is used to optimize the region of original crisscross frequency-domain feature set which includes 240 features and space-domain feature set which includes 82 features.

In order to find a best fitness function for genetic algorithm, we tried to use mutual information entropy as fitness function. It is known that the object function of mutual information entropy is a problem of the largest values. Based on experiments, and according to analysis of surface defects of steel strips, mutual information entropy is made as fitness function of genetic algorithm, and it is shown as equation (39);

$$I(E, F) = \frac{1}{N} [I^*(E, F) - I(F)]$$

$$= \frac{1}{N} \left[\sum_{i=1}^n \sum_{j=1}^N I(w_i, x_j) - \frac{1}{N-1} \sum_{i=1}^N \sum_{j=1, j \neq i}^N I(x_i, x_j) \right] \quad (39)$$

where

$$I(w_i, x_j) = \sum_{k=1}^K p(w_i, x_{j,k}) \bullet \log \frac{p(w_i, x_{j,k})}{p(w_i) \bullet p(x_{j,k})} \quad (40)$$

$$I(x_i, x_j) = \sum_{h=1}^K \sum_{k=1}^K p(x_{i,h}, x_{j,k}) \bullet \log \frac{p(x_{i,h}, x_{j,k})}{p(x_{i,h}) \bullet p(x_{j,k})} \quad (41)$$

3.4 Local border search algorithm

According to the statistics of cold rolled strip, there are more than 30% defects in border region, therefore how to extract the border from acquired images fast and accurate is very important for defect detection. Figure 27 shows a local pixel image with a 45° border. From the figure, it can be seen that the next border point will arise in one neighbor pixel, and if the border angle is smaller than 45°, the next border point will arise among on neighbor pixel. Therefore, the next border point must be found if let the algorithm search a small neighbor region such as 3 pixels, and here bring forward Local Border Search Algorithm (LBSA) as follows. Figure 28 is flow chart of the new algorithm.

After the algorithm finishes, the border can be get, and every horizontal border point coordinates can be expressed with equation (42) and vertical border point coordinate can be expressed with equation (43).

$$(x, a[x]) \quad x = 0, 1, 2, \dots, Width - 1 \quad (42)$$

$$(a[y], y) \quad y = 0, 1, 2, \dots, Height - 1 \quad (43)$$

Fig. 27. A local pixel image with a 45 border

Fig. 28. Flow chart of Local Border Search Algorithm (LBSA)

For some complicated border types shown as Figure 33, it can be get both two horizontal and vertical border lines with equation (44), and then utilize the condition as equation (45) to calculate the point of intersection(X,Y) of the two border line, and the valid region of strips can be achieved.

$$\begin{cases} (x, a[x]) & x = 0, 1, 2, \dots, Width-1 \\ (b[y], y) & x = 0, 1, 2, \dots, Height-1 \end{cases} \quad (44)$$

$$\begin{cases} x = b[y] \\ y = a[x] \end{cases} \quad (45)$$

Fig. 29. Left border image of cold rolled strips

For example, Figure 29 is a 756×141 cold rolled strip image, and the valid region of steel strip lies in the left part of the image. When input the image into the Local Border Search Algorithm and give its border type, the algorithm can firstly search from right of row 0 with the coordinates of $(755, 0)$, till first border point is found, and records the horizontal coordinate $a[0]$, it will meet the condition $|f(a[0], 0) - f(a[0] + 1, 0)| > T$. After that the algorithm can search the next border point with a given scope of $TScp = 3$, and the search scope of row 1 is $[a[0] + 3, a[0] - 3]$, and the border point must be appeared in the small region, so that a point $(a[1], 1)$ can be found and it will meet the condition of $|f(a[1], 1) - f(a[1] + 1, 1)| > T$. Similarly, the algorithm can run row by row till all border point are found, and get all the coordinates $a[2]$, $a[3]$, $\dots$, $a[139]$, $a[140]$, and at last, the search result is as Figure 30. With the same method, other border type can be achieved.

Fig. 30. Extraction result of Figure 2 (b) by LBSA

(a) Extraction result by Local Border Search Algorithm

(b) Extraction result by traditional algorithm

Fig. 31. Contrast effects of extraction results

Fig. 32. Extraction result left valid region with right border which is near the border of the image

Fig. 33. Extraction result of complicated border type of top-right border

Figure 31 is the contrast effects of extraction result for the same image with different algorithm, and Figure 31(a) is extracted by Local Border Search Algorithm (LBSA), and Figure 31(b) is extracted by traditional Gray Level Gradient Threshold Algorithm (GLGTA). It can be seen that there are some noise inside Figure 31(b) but the effect is very perfect in Figure 31(a). Figure 33 shows the extraction result of complicated border type of top-right border. Table 1 shows the contrast effects of extraction results from 300 right border images, and it can be seen that the speed of the new algorithm is increased over 22-220 times than the traditional algorithm.

Sample image	Distance between strip border and image border (Pixels)	Time cost of Gray Level Gradient Threshold Algorithm (T1: ms)	Time cost of Local Border Search Algorithm (T2: ms)	T1/T2 (times)
Fig. 30	Greater than 600 pixels	2.0~2.2	0.01~0.03	67~220
Fig. 32	Smaller than 200 pixels	0.65~0.75	0.01~0.03	22~75

Table 1. Contrast table of right border extraction

Although Local Border Search Algorithm is more advantageous in search accuracy and speed of border than traditional algorithms, it is still short in some aspects. The main shortages are: (1) It is strongly dependent on prior knowledge; (2) It is sensitive to initial point.

In order to overcome the weaknesses above, deep research is carried out mainly from following three aspects:

1. Introducing a small neighborhood to the algorithm

Changing comparison between pure pixels to two small neighborhoods, generally, the neighborhood can be selected as a $m \times n$ ($m > 0, n > 0$) regular area or crisscross area. Then by calculating average of neighborhood or median etc. replace old gray value with the result. After improving it, the algorithm can remove disturbance of local noise, raise accuracy of border, and make the algorithm owning a higher quality of anti-noise. The neighbors can be chose as Figure 34.

Fig. 34. Neighbor region in common use, (a) Square neighbor; (b) Horizontal neighbor; (c) Vertical neighbor; (d) 3×3 strong connection neighbor; (e) 3×3 weak connection neighbour

2. Modifying search rules of initial point

Whenever the gray value change reaches a given threshold value, recording the point as initial point of border. If there is no such point, enter next loop till such point appears. The advantage of this method is that we can find the border point even with no gray changes.

3. Adding judgment rule of ending point

Defining wrong permitting search times in Local Border Search Algorithm, if no border ending point is found in the scope of wrong permitting search times, the algorithm continues, when there is no border ending point is found beyond the scope of wrong permitting times, the algorithm stops.

After improving Local Border Search Algorithm from the three aspects above, the expanded algorithm can still keep the complexity as $O(n)$, and meanwhile, it can be used to detect high contrast defects of cold rolled strips fast and accurately, and can be used as fast thinning algorithm of image.

3.5 Defect classification techniques

Artificial neural network is a parallel distributed information processing system. It is a network constituted by many processing units which are connected each other by unidirectional signal path. These processing units are called artificial neural units, and have the abilities of local memory and local information processing. Every processing unit outputs to an expected connection unidirectionally and transmits the same signal which is called output signal of processing unit. The output signal of processing unit can be any demanded mathematic types. Under complete local constraint circumstances, information processing executed in every processing unit can be any definition, namely the information processing depends only on the memorized value of itself and current value of the input stimulated signal of the processing unit. Neural network is an abstraction and simplification of human brain in microstructure and function, and reflects some fundamental characters such as parallel processing, learning, association, pattern classification, memory, and so on.

Obviously, according to the above characters of neural network, applying neural network to surface defect recognition of cold rolled strips is a good choice. In the application, LVQ neural network (Kohonen, T., 1992) is applied to recognize the defects.

1. LVQ neural network

LVQ neural network consists of 3 parts such as input layer, hidden layers and output layer. The hidden layer is also called competitive layer or Kohonen layer, and it is completely linked between input layer and hidden layer but just partly connected between hidden layer and output layer, and every output neuron is connected with different group of hidden neuron. The training process of LVQ neural network is in fact a process of continually competition and weight updating process among all neuron units of hidden layer. Figure 35 is topological structure of LVQ neural network.

Given a sequence of input documents, an initial group of reference vectors w_k is selected. In each iteration, a x_i document is selected and the vectors w are updated, so that it will adapt better to x_i . The LVQ algorithm works as follows.

For each class k , a weight vector w_k is associated. In each repetition, the algorithm selects a x_i input document and compares it with each weight vector w_k , using the Euclidean distance $\|x_i - w_k\|$, so that the winner will be the weight vector w_c nearest to x_i , with c as the index of that weight vector:

$$\|x_i - w_c\| = \min_k \{\|x_i - w_k\|\} \quad (46)$$

The classes compete among themselves in order to find which is most similar to the input vector, so that the winner will be that one with less euclidean distance with respect to the input document. Only the winner class will modify its weights using a reinforced learning algorithm, either positive or negative, depending on whether the classification is correct or not. Thus, if the winner class belongs to the same class as the input vector, it will increase the weights, moving slightly closer to the input vector (prize). On the contrary, if the winner class is different from the input vector class, it will decrease the weights, moving slightly further from the input vector (punishment). Let $x_i(t)$ be an input document at time t , and $w_k(t)$ the weight vector for the class k at time t .

The following equations define the basic learning process for the LVQ algorithm:

$$w_c(t+1) = w_c(t) + s \cdot \alpha(t) [x_i(t) - w_c(t)] \quad (47)$$

where $s = 0$, if $k \neq c$; $s = 1$, if $x_i(t)$ and $w_c(t)$ belong to the same class; and $s = -1$, if they are not the same class. Where $\alpha(t)$ is learning rate, always between 0 and 1, is a monotonically decreasing function of time. It is recommended that $\alpha(t)$ should initially be rather small, especially smaller than 0.1, and $\alpha(t)$ continues decreasing to a given threshold u , very close to 0. Usually, $\alpha(0)$ is always initialized in 0.005, decreasing linearly to $u = 0.001$, according to the following equation where K is the number of classes :

$$\alpha(t+1) = \alpha(t) - \frac{\alpha(0) - u}{K} \quad (48)$$

Fig. 35. Topological structure of LVQ neural network

2. Parameter optimization method of neural network

In order to choose best parameters for neural network, traditional methods are all decided by experience, but in fact, these parameters are not optimized parameters, a new parameter optimization method of neural network is put up here, and it can settle the problem perfectly.

The new parameter optimization method of neural network is aiming at finding inner parameters for describing practical problem based on small-samples(Tang, B., 2003), so that the parameters can meet the solution of the problem, and it makes possible for avoiding blindly finding possible parameters of neural network. Figure 36 shows the flowchart of the new parameter optimization method based on small-samples.

Fig. 36. Flowchart of parameter optimization algorithm

1) Extraction of small-samples

In order to make parameters reflect the essence of practical problem, a certain proportion of samples is extracted from all the samples to form a new sample aggregation, named small-samples, and let the proportion be η . We supposed that the original sample aggregation is P_0 as equation (49).

$$P_0 = \{X_1, X_2, \dots, X_n\} \tag{49}$$

The amount of every item inside the original sample aggregation is $p_0^1, p_0^2, \dots, p_0^n$ respectively. At the same time, we supposed that the new sample aggregation is P_s as equation (50)

$$P_s = \{X'_1, X'_2, \dots, X'_n\} \quad (50)$$

Its amount is N , therefore the extraction rule is defined as following:

Extracting every class of samples by its proportion from sample library, and defining the number of every sample as p_s^i , therefore it can describe as equation (51).

$$p_s^i = \frac{p_0^i}{\sum_{j=1}^n p_0^j} N \quad i = 1, 2, \dots, n \quad (51)$$

Consequently the distribution law of extracted new small-samples P_s is the same as original samples P_0 , in another word that the extracted small-samples can stand for the original samples to some extent, and the parameters of neural network selected under such small-samples can express the map relationship of the neural network under the whole original samples. Such small-samples selected by the method are so called proportional samples. A group of training small-samples p_{s1} and testing small-samples p_{s2} can be extracted in the practical application.

2) Parameter segmentation and uniform encoding

When applying it to practical engineering project, firstly it is necessary to know all the parameters of neural network, and choose the parameters which are related with the essence of problem among all the parameters. Now defining the number of selected parameters as p , and all parameters are independent and have no relation with samples theoretically, in another word that the selected parameter variables can reflect the essence characters of the practical problem. After determined parameters which need be optimized, it is time to segment all the parameters under a scope of experience values or theoretical values.

Supposed that all these p parameters are divided into such parts respectively as $C_1, C_2, \dots, C_p$, then combining all the parameters under unrepeated rule, and there are total M combinations, it can be described as equation (52):

$$M = \prod_{i=1}^p C_{C_i}^1 \quad (52)$$

What come on next? We must encoding the parameters for every combination, and assign a number to it as $1, 2, \dots, M$. There are mainly 2 steps in this stage as following:

Firstly, determining the order of every parameter and fixing its position from the front to the back. Figure 37 shows the exact order of every parameter in the same group.

P_1	P_2	...	P_M
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Fig. 37. Exact order of every parameter

Secondly, a uniform serial number is given to every combination. When a specific number is given to a front parameter, the back parameter will traverse all possible values, and the number will increase 1 step by step till all M possibilities is finished, and the encoding finished.

3) Automatic training circularly and plotting polyline figure

After encoding all the parameters, an automatic program must be developed, and every group of parameters is used as parameters of neural network respectively to do training and testing. The procedure can be described as followings:

- a. Take out one specific group of parameters as parameters of neural network.
- b. Training the neural network with the training small-samples of P_{s1} .
- c. When the training finished, saved the trained neural network model for testing.
- d. Testing the neural network with testing small-samples P_{s2} .
- e. Making a statistic of its recognition rate.
- f. Repeating step “a” to “e” again till all M group of parameters are traversed for one time.
- g. Using the M recognition rate values under different M group of parameters of neural network to plot a polyline figure on a coordinate system.
- h. Finding the peak recognition rate value of the figure, and writing down its related group number of parameters which is selected as the final parameters of neural network under the original samples.

4. Application and experiments

Table 2 is samples distribution table which are all acquired by surface defect online inspection system of cold rolled strips from locale of certain production line in China. From the table, it can be seen that there are total 12 classes of defects of cold rolled strips, and there are total 6360 original training samples and 3180 original testing samples.

According the extraction rule of small-samples of parameter selection method described in preceding part, a training small-samples aggregation P_{s1} and a testing small-samples aggregation P_{s2} will be get from original training samples and testing samples under a given extraction proportion of 8% and 4% respectively.

Item	Scratches	coil Breaks	point sticks	Feathers	white spots	roll Imprints	edge Foldings	rusts	Emulsion marks	Orange peels	edge Cracks	other	sum
Number of training samples	1223	1398	1203	1153	463	295	193	121	89	80	70	71	6360
Number of testing samples	612	699	602	577	232	147	96	61	45	40	35	35	3180

Table 2. Samples distribution table of system

For LVQ3 neural network, the number of neurons in compete layer must be determined firstly, and according the system, it is assigned 106. Secondly, make sure that there are three parameters which are related with the essence of described system, they are initial learn rate $\eta(0)$, relative learn rate ε and window width m . According to the experience of LVQ3 neural network, the experience scope of all the three parameters can be described as equation (53).

$$\begin{cases} 0.01 \leq \eta(0) \leq 0.1 \\ 0.05 \leq \varepsilon \leq 0.3 \\ 0.1 \leq m \leq 0.5 \end{cases} \tag{53}$$

After experiments, polyline will be plotted under coordinates of recognition rate and parameter combination number as shown in Figure 38. It can be seen that the coordinate (48, 96.2%) stands for the peak point in the figure, it means that No. 48 parameter combination can describe the practical problem better than other parameter combination of LVQ3 neural network, and the test result can reach the highest recognition rate of 96.2%. By decoding we can get the parameters of LVQ3 neural network as Table 3.

Fig. 38. Curve of optimized parameter selection of LVQ3 neural network

It can be seen from Table 4 that the recognition rate under No.1 group of parameters reaches to 89.69%, and it is the highest in table, but under other 7 group of parameters, the recognition rates are all lower than it. Therefore, the experiments here fully proved that using the optimized parameters of neural network by the new parameter selection method as the parameters of neural network, the classification information can be expressed more accurately, a higher recognition rate can be get when applying to recognize surface defect of cold rolled strips.

Item	Neuron number of input layer	Neuron number of competition layer	Neuron number of output layer	Initial learn rate $\eta(0)$	Relative learn rate ε	Window width m	Iteration times
Value	22	1276	12	0.05	0.1	0.3	51040

Table 3. Parameters of LVQ3 neural network

No.	Training condition			Testing result		
	$\eta(0)$	ε	m	Number of correct recognition	Recognition rate	Difference with No.1
1	0.05	0.1	0.3	2852	89.69%	0.00%
2	0.01	0.05	0.1	2493	78.40%	11.29%
3	0.1	0.3	0.5	2598	81.70%	7.99%
4	0.08	0.2	0.4	2530	79.56%	10.13%
5	0.03	0.3	0.2	2645	83.18%	6.51%
6	0.06	0.08	0.3	2791	87.77%	1.92%
7	0.01	0.3	0.1	2609	82.04%	7.65%
8	0.05	0.1	0.5	2755	86.64%	3.05%

Table 4. Recognition results under different neural network parameters

5. Conclusion

An online surface inspection system of cold rolled strips is researched based on multimedia technology such as image process technology and pattern recognition technology, and it is applied to a production line of a certain iron & steel corporation in China, which includes cameras, illuminations, parallel computer systems and other correlative parts, and can detect and recognize over 10 main defects of cold rolled strips real time. The application effects show that the system can meet most requirements of corporation, and it can detect defects stably for long time. With the improvement of algorithm, some difficulties will be overcome, and the system will become wider use.

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Multimedia technology will play a dominant role during the 21st century and beyond, continuously changing the world. It has been embedded in every electronic system: PC, TV, audio, mobile phone, internet application, medical electronics, traffic control, building management, financial trading, plant monitoring and other various man-machine interfaces. It improves the user satisfaction and the operational safety. It can be said that no electronic systems will be possible without multimedia technology. The aim of the book is to present the state-of-the-art research, development, and implementations of multimedia systems, technologies, and applications. All chapters represent contributions from the top researchers in this field and will serve as a valuable tool for professionals in this interdisciplinary field.

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University Campus STeP Ri
Slavka Krautzeka 83/A
51000 Rijeka, Croatia
Phone: +385 (51) 770 447
Fax: +385 (51) 686 166
www.intechopen.com

InTech China

Unit 405, Office Block, Hotel Equatorial Shanghai
No.65, Yan An Road (West), Shanghai, 200040, China
中国上海市延安西路65号上海国际贵都大饭店办公楼405单元
Phone: +86-21-62489820
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