Stripe Surface Defect Image Recognition by Supervised Tree ISOMAP and Incremental GRNN

Shengfeng Gan
Geophysics & Geomatics, China University of Geoscience, Wuhan, China
Corresponding author, Email: gsfxm@aliyun.com

Lin Sun, and Dianhong Wang
Communication and Information Sciences, China University of Geoscience, China
Email: youxiangshouhu2011@sohu.com, 66497569@qq.com

Abstract—The new isometric mapping dimensionality reduction algorithm with Incremental Generalized Regression Network has been primarily recognized for stripe surface defects images with the typical characteristics of complex texture, non-uniform image size, asymmetrical number of sample classes, variation illumination environment. This method is suitable to resolve the problem of “short circuit”, stored internal structure in lower dimension space. In addition, the algorithm parameters influence on the stripe surface defect images is greatly reduced. The finally experiment results show that it is effective and efficient for stripe surface defects with the highest recognition rate of stripe surface defect can reach to 97%, and the highest recognition rate of complex stripe surface defect can reach to 74%.

Index Terms—Surface Defect Image Recognition; Supervised Tree ISOMAP; Incremental Generalized Regression Network

I. INTRODUCTION

Strip surface defect image detection and recognition is one of the most important fields of strip quality-control. The related technologies are increasingly concerned about strip engineer recently. Especially, the applications on the process before rolling and finished product (i.e. detection before Pickling-CC Rolling, finished product detection etc.) [1].

Unfortunately, complex texture, non-uniform image size, variation environment and more mixed defects are the typical characteristics of the strip surface defect image. Many image recognition methods are not competent for it. The direct reason is the insufficiency of capability of dimensionality reduction method. For example the method base on extraction of lower property of image feature and image characteristic space transformation dimensionality reduction method [2].

In this paper, we aim at the Strip surface defect image characteristic above, and suggest on using image direct dimensionality reduction methods, which combine isometric mapping dimensionality reduction (ISOMAP and ST-ISOMAP) with Incremental Generalized Regression Network. In this way, separable lower-dimensional characteristic space for image could be captured. So, direct dimensionality reduction methods are benefit to distinguish between categories. It also could fit to distinguish complex strip surface defect image that affect the quality and production process.

Two key factors that determine the successful application of direct dimensionality reduction method are: (1) image interest area resizing [3]. Dimensionality reduction process needs the same size of sample, but the size of strip surface defect images is non-uniform. For include all important information of defect and preserve interest area where need choose a appropriate image size for dimensionality reduction. Face image is 80pixel *60pixel usually [4]. (2) preserved the intrinsic structure in a low dimension space as well as possible. Asymmetrical number of sample classes and small sample always bring the difficulty to high dimensionality reduction. Especially, some classes of strip surface defect image are low number and the other have large member.

In terms of the first above mentioned key factor, Geometric Transformation, as the general solution method, has helped in achieving all image information collection when the image resizing is appropriate. In recent years, nonlinear resizing method (e.g. fisheye-view warp, seam carving) have benefit to save important information, although time consuming. These methods change the structure of image, but preserve image interest area, and have good performance in aspects of integrality and coherence. Thus, image interest area resizing can be considered that this key factor has been satisfactorily investigated.

On the other hand, many methods could preserve the intrinsic structure in a low dimension space. But they aimed at face image with 4800-dimension or lower and asymmetrical number of sample classes. There is no analogous surface defect image progress in terms of the second key factor. To meet this goal, we apply isometric mapping dimensionality reduction techniques to embed
the strip surface defect images space into a low-dimensional space. Our results demonstrate that the intrinsic structure in the original space have been preserved in an adequate way. We also show that the proposed approach outperforms the linear dimensionality reduction methods, such as Locality Preserving Projections (LPP) [5].

Three stages must be implemented by Strip surface defect image recognition process. Step1: In terms of Strip surface defect image size distributing, choose uniform image size, and resize it. Step2: Apply isometric mapping dimensionality reduction techniques to embed the Strip surface defect image space into a low-dimensional space. Step3: classify in the low-dimensional space with some well classifier. Than analyze the result.

The rest of this paper is organized as follows. Section 2 describes the related work. In section 3 we present the proposed approach. Section 4 contains three recognition process stages of Strip surface defect image and detailed experimental result. Finally, section 5 concludes this paper.

II. RELATED WORKS

In point of development of strip surface defect detection and recognition, computer vision have been widely applied since 1996 [6], at the same time, large number of new image process algorithms have been exploited for strip surface defect detection stage by stage [7]. As one of the most important parts, strip surface defect image recognition technology have attracted strip engineer. Structure spectrum method, fraction dimensions based on the optimized scale, amplitude spectrum method, Wavelet method combine with powerful classifier, such as SVM, Neural Networks, Weak Classifier Adaptive Enhancement Classification method [8], have been used for recognizing many different kinds defect in Plates and Hot-Rolled steel strips. Many of these applications have well effect. Now Roberto Medina have introduced Fourier combine with Gabor filters for image feature extraction, and used k-nearest neighbor for flat steel coils classification in 2011. The defect recognition rate is 87% [9].

In point of data dimensionality reduction technology, principal component analysis (PCA) and independent component analysis (ICA) are the conventional technology for dimensionality reduction, and are easy to implement. Unfortunately, PCA and ICA need to compute all the covariance matrix of data, and cannot adapt to industry classification due to the distributions of most real-world data are nonlinear. Since two novel methods about nonlinear dimensionality reduction method have been published in 2000: Isometric mapping (ISOMAP) and Local linear embedding (LLE) [10], [11], [12], extensive algorithms base on these two novel methods have been illuminated to solution face recognition, hand images recognition, and handwritten mages recognition [13]. But it is unduly restrictive that these algorithm experiments base on the subsets which are convex. Real-world data, in general, are identical on some dimension. LLE method may raise redundancy in data dimensionality reduction. Hessian Locally Linear Embedding (HLLE) can solution the problem of non-convex data, but for the high dimension and high sample data space, the cost of compute is also large. So HLLE is not easy for solution the Strip surface defect image recognition problem [14]. Otherwise, Ref. [11] has a research on dimensionality reduction parameter Embedding neighbor k, Embedding dimensionality; Guy Rosman implied topologically constraining isometric embedding (TCIE) for non-convex data dimensionality reduction [15]. Dimitris Rafailidis has applied isometric mapping method to efficiency of audio similarity [16];

In contrast with these strip surface image process method, isometric mapping dimensionality reduction method more benefit to preserve strip surface image intrinsic structure than other feature extraction methods; In contrast with nonlinear dimensionality reduction technology application especially to Strip surface defect image recognition, isometric mapping and its improved algorithms have more adaptability than others.

III. ISOMETRIC MAPPING DIMENSIONALITY REDUCTIONS FOR STRIP IMAGE

A. Manifold Structure of Strip Surface Defect

There are much non-linear geometry in the actual reality of the strip surface defect images. In the cold-rolled strip steel, for example, illumination brightness regional property of double-skin is curve geometry (Fig. 1).

As the same as illumination brightness regional, many defect image properties, such as image density, grayscale position, are non-linear distribution. If extended images to multiple properties, the distribution must be high-dimension non-linear. For this reason, we can suggest that strip surface defect images contain wealth of non-linear geometry, and nonlinear dimensionality reduction method is more appropriate for preserve manifold structure.

![Figure 1. The 1-dimension distribution about illumination brightness regional (The gradual change illumination brightness regional, from bottom to top)](image)

B. ST-ISOMAP for High-dimensionality Reduction

Supervised Tree ISOMAP (ST-ISOMAP) based on classical multidimensional scaling theory (MDS) and S-
ISOMAP [17]. It preserves the relationship between images $X_i$ and $X_j$ through local or global linear. Utilized this relationship mapping $R^0$ to $R^d$, $D$ is dimension of original space, $R^d$ is a d-dimensional Euclidean space ($d << D$). We can see that $R^d$ Euclidean space that best represent the intrinsic geometry of the data, and the $R^d$ Euclidean space classification effect will better than $R^0$.

In this algorithm, we suppose the image dataset $M$, the number of $M$ is $n$, and the image classifications is $Y; k=1,2,\ldots, n$; every pixel of each image compose original space $R^0$. Let $d(X_i, X_j)$ be a Euclidean distance between a pair of images $X_i$ and $X_j$ belonging to image dataset $M$. Define the dissimilarity between two points $X_i$ and $X_j$ as

$$D_e(X_i, X_j) = \sqrt{1 - e^{-d(X_i, X_j)}} \quad Y_i = Y_j$$

$$D_d(X_i, X_j) = \sqrt{1 - e^{-d(X_i, X_j)}} - \alpha \quad Y_i \neq Y_j$$

where the parameter $\beta$ is used to prevent $D_e(X_i, X_j)$ to increase too fast when $d(X_i, X_j)$ is relatively large, $0<\beta<1$, the parameter $\alpha$ is used to decrease the distance between class and class.

Given L-classes known images in the $R^0$, with class label matrix label(L), $L=1,2,\ldots, n$. Let $i$ and $j$ are different inter-class images; $i$ and $i'$ are different intra-class images, then inter-class Euclidean distance defined as $d(x_i, x_j)$, intra-class Euclidean distance defined as $d(x_i, x_j)$. Connection neighborhood graph with following conditions: minimum Euclidean distance between inter-class points, the inter-class neighborhood graph connect by

$$D_{min}(i, j) = \min_{i=1, j=1}^{L}(d(x_i, x_j))$$

$L1$ and $L2$ are the different class label. Then given matrix LM, which storage the minimum Euclidean distance between inter-class points, with symmetric matrix

$$LM = \{D_{min}(i, j)\} \quad i, j \in L$$

Find $\exists d(x_i, x_j) = D_{min}(i, j)$, build up the connection neighborhood graph between $i$ and $j$. If there are serials pairs of inter-class points, connection all the neighborhood graph.

The results of S-ISOMAP and ST-ISOMAP on 2-class Roll-swiss can be show in Fig. 2. There are clear present on connection neighborhood graph, which enable to reduce the "short circuits" and enhance the classification level.

Obviously, $D_e(X_i, X_j)$ hold inter-class and increasing intra-class distance. If edge lengths replace $d(X_i, X_j)$ with $D_e(X_i, X_j)$ to denote the distance between two points $X_i$ and $X_j$, it will building up a new distance matrix, which could compute a new neighborhood graph $G$ for dimensionality reduction. The detailed steps of ST-ISOMAP are listed as follows:

Step 1. For each image, Construct neighborhood graph: Define the graph $G$ over all data points by connecting points $X_i$ and $X_j$, if they are closer than a certain distance $\varepsilon$, or if $X_i$ is one of the k-nearest neighbors of $X_j$. Set edge lengths equal to $D_e(X_i, X_j)$.

Step 2. Compute shortest paths of each pair of the graph $G$: Initialize

$$dG(x_i, y_j) = D_e(X_i, X_j)$$

If $X_i$ and $X_j$ are linked by an edge; $dG(x_i, y_j) = +\infty$ otherwise. The matrix of final values

$$DG = \{dG(x_i, y_j)\}$$

It contains the shortest path distances between all pairs of points in $G$.

Step 3. Apply MDS on $DG$; construct $d$-dimensional embedding, to embed $X$ to a point $y$ in $R^d$.

There is some definite advantage about ST-ISOMAP. Firstly, the inter-class distance is larger than the intra-
class distance, which makes $D_i(X_i, X_j)$ suitable for classification tasks. Secondly, no matter how strong the noise is, inter-class and intra-class distance can be controlled in certain ranges respectively. Finally, $D_i(X_i, X_j)$ function is monotone increasing with respect to the Euclidean distance. This ensures that the main geometric structure of the original data set.

There are 2-dimensional dimensionality reduction experiments with the different algorithms ISOMAP and ST-ISOMAP, which experiments data come from Strip surface defect image dataset (Fig. 4). The result and visualization effect can be show on figure 1. Then we can imply that, with ISOMAP algorithm (Fig. 3(a)), a majority of images with same class cluster in two or three spaces, and the different classes are divisible, while the process is not very easy and the result may be imperfect.

We also can suggest that, with ST-ISOMAP algorithm (Fig. 3(b)), different classes are far from each other, except the distance between hole defect images and indentation defect images, which inter-class distance is as same as intra-class distance. However we can also consider that ST-ISOMAP has well ability of class division.

![Two-dimensional Isomap embedding (with neighborhood graph).](a)

![Two-dimensional Isomap embedding (with neighborhood graph).](b)

Figure 3. The visualization effect of 2-dimensional embedding in $\mathbb{R}^2$ (Let embedding neighbor $k=35$, number of landmark in MDS, note by Landmark=50, the defect classes are edge crack (red), double-skin (cyan), scar (yellow), hole (black), indentation (blue), a is the result of ISOMAP, and b is the result of ST-ISOMAP).

C. Incremental Generalized Regression Network (IGRNN)

Generalized Regression Neural Network (GRNN) has better generalization performance [18]. Thus the incremental GRNN is suggest in this paper. Let $f(x, y)$ as the Joint Probability Density function of random variable $x$ and $y$. If $x = x_0$ and $y = y_0$, the return value is:

$$
\hat{y}(x_0) = \frac{\int_{-\infty}^{\infty} y f(x_0, y) dy}{\int_{-\infty}^{\infty} f(x_0, y) dy}
$$

(7)

Estimated density function $f(x_0, y)$ on sample data sets $(x_i, y_i)_{i=1}^{n}$ by Parzen non-parametric estimation:

$$
f(x_0, y) = \frac{1}{n \pi^{\frac{d}{2}}} \sum_{i=1}^{n} e^{-d(x_0, x_i)^2} e^{-d(y, y_i)}
$$

(8)

where

$$
d(x_i, x_j) = \sqrt{\sum_{i=1}^{d} [(x_{ij} - x_{ij})^2]}
$$

(9)

And $n$ is sample size, $p$ is the dimension of $x$, $\sigma$ is the width coefficient of the Gaussian function. According to (7) and (8)

$$
\hat{y}(x_0) = \frac{\sum_{i=1}^{n} y_i e^{-d(x_0, x_i)^2}}{\sum_{i=1}^{n} e^{-d(x_0, x_i)^2}}
$$

(10)

Because of $\int_{-\infty}^{\infty} ze^{-z^2} dz = 0$, the result of neural network simulation model is:

$$
\hat{y}(x_0) = \frac{\sum_{i=1}^{n} y_i e^{-d(x_0, x_i)}}{\sum_{i=1}^{n} e^{-d(x_0, x_i)}}
$$

(11)

where the output value is $\hat{y}(x_0)$ and the weights of $y_i$ is $e^{-d(x_0, x_i)}$. If $x_i$ = $i$, $i=1, 2, \cdots, m$ and output value $\hat{y}(x_0)$ $j=1, 2, \cdots, n$ that $n << m$ are known, the summation layer $y_j$ and its weights $e^{-d(x_0, x_j)}$ are easily to be computed. Then the input increments are defined as $x_i$ : $\Delta=1, 2, \cdots, k$, the simulation model of incremental data can be listed as:

$$
\hat{y}(x_{0j+\Delta}) = \frac{\sum_{i=1}^{m} y_j e^{-d(x_0, x_i)}}{\sum_{i=1}^{m} e^{-d(x_0, x_i)}} : 0 j + \Delta = 1, 2, \cdots, n
$$

(12)

The incremental data and original data will work together in (12) and this output value has the same dimensions with $\hat{y}(x_0)$.
Let the training dataset as \( R^o \), test dataset as \( R^{\text{test}} \) before classification. The classification label of \( R^o \) are known to us, and \( R^{\text{test}} \) are unknown. The training dataset and test dataset cannot be embed to \( R^d \) at same time, due to the class label of test dataset are unknown. Hence, we construct a regression using neural network to approximate the unknown mapping process of training dataset. Using this regression to test dataset, test dataset will be embedding to lower space \( R^d \) where \( d' = d \). Due to the same mapping method, training dataset and test dataset have all preserve the same data intrinsic structure. Otherwise, the result will be incorrect. The detail of classification method can be list as follows:

1. Map the training data \( R^o \) into a lower dimensional space \( R^d \) using ST-ISOMAP.
2. Construct IGRNN to approximate the mapping.
3. Map the test data \( R^{\text{test}} \) into a lower dimensional space \( R^d \) (\( d' = d \)) using IGRNN.
4. Predict test data classification in d-dimensional space using classification methods that including k-NN, decision tree C4.5, SVM [19], [20].

IV. EXPERIMENTAL RESULTS

A. Surface Defect Image Analysis

Surface defect image are collected by linear array cameras which have 2492 pixel each line, and 1800mm maximum line scan distance. The main surface defect image is collected from stripe surface defect images and come from Wuhan Iron and Steel Company (WISCO) in different work periods, total number is 432, which construct the original image dataset \( M_{432} \). Based on the effect on production, we define the images into 5 classes: 24 edge crack defect images, 87 double-skin defect images, 74 scar defect images, 51 hole defect images, 196 indentation defect images. Main characteristic of surface defect image can be show in figure 2. Firstly, asymmetrical number of sample classes. The proportion of edge crack and hole is very small; on the contrary, number of indentation is large. Secondly, inter-class dissimilarity is definitely large, but intra-class noises have more negative effect on dimensionality reduction.

In addition, surface defect image size is non-uniform (Fig. 5), most of images size are below 500 pixel *200 pixel. However the horizontal pixel of many important defects image size are beyond 650 pixel, such as continuous hole; And the vertical pixel of many important defects image size are beyond 2600 pixel, such as double-skin. For preserving image interest area, invariant image and intrinsic structure of the \( M_{432} \) data, image resizing must choose the mean of all images. Define \( \text{PIX}_{kH} \) and \( \text{PIX}_{kV} \) as normalized horizontal pix and vertical pix. Computing the resized image size is \( \text{PIX}_{kV} \), \( \text{PIX}_{kH} \) = (232,143). Stripe surface defect images with size of 232 pixel *143 pixel can preserve image interest area definitely (Fig. 1). Then there is another problem with high dimensional stripe surface defect image dimensionality reduction, because that the single image dimension is 33432. Now we construct original space of \( M_{432} : R^{33432} \) (33432*432 matrixes) which each column is an image data point.

B. Parameter Selection

In this section, we map \( R^{33432} \) into a lower dimensional space using ISOMAP and ST-ISOMAP. In addition, capture the appropriate d-dimensional space through experiments, which not only preserves manifold structure in the integrity, but also decreased the d to lower enough.

Experiment with several parameters, including Landmark, embedding neighbor k and embedding dimensionality. Let d-dimensional space \( d=30 \), track record residual variance between \( R^{30} \) and \( R^{33432} \) (shown in Fig. 6(a)). Although studying on residual variance are benefit to capture low dimensional space, it cannot be used to instead recognition rate research, due to variation of inter-class distance (Fig. 3).

The mentionable thing is embedding neighbor k in ST-ISOMAP. When \( k<24 \), ST-ISOMAP only obtain some discontinuous manifold area in \( R^{33432} \) and construct more than two neighborhood graphs. However, the dimensionality reduction will fail when there are more than two neighborhood graphs. To ensure the correct dimensionality reduction of the ST-ISOMAP method, we need to embed neighbor \( k>24 \). In this paper, we only...
show the residual variance result with embedding neighbor $k=30$ and Landmark=$50,200,300$ (Fig. 6(b)).

The residual variance result can be implied as follows:

1. The S-ISOMP dimensionality reduction method has adapted to high-dimension stripe surface defect images, which contain a wealth of geometry. And the method could embed an integral geometry to lower than $20$-dimension.

2. When only one neighborhood graph is created, the residual variances close, although Landmark and different embedding neighbor $k$ are different.

3. After dimensionality reduction using ISOMAP, residual variances with same Landmark are monotone decreasing. $R^{20}$ can preserve enough manifold structure for $R^{13412}$. We can choose the low space for classification from $2$ to $20$ (Fig. 6(a)).

4. For using ST-ISOMAP, residual variance will be invariable more than $3$ dimensions (Fig. 6(b)), and the residual variance definitely lesser than the value from ISOMAP. However, we need more dimensions for classification when inter-class distance lesser than intra-class distance (Fig. 3(b)). Hence we can choose the low space for classification from $3$ to $20$.

C. Recognition Results of Different Testing Data

The recognition results are shown on Fig. 6, when training dataset set as the test dataset. After dimensionality reduction by the ISOMAP, the results show in Fig. 7(a) that the number of Landmark has small effect on the defect recognition rate, and the effect is the best when the number of Landmark is half of total training database. Combination of Fig. 6(a) and Fig. 7(a), we also can find that the residual variance basically can reflect defect recognition effect. And Fig. 7(b) shows that defect recognition rate obviously arise with the number of dimensionality, until $d>10$, it means that $10$-dimensional space ($R^{10}$) can save the intrinsic structure of $M_{432}$ enough. Then in Fig. 6c, we can suggest that the embedding neighbor $k$ have lower effect on defect recognition rate when the number of Landmark is big enough in $20$-dimensional space. After dimensionality reduction by the ST-ISOMAP, even though choice different parameter, the defect recognition rates maintain at $99.7\%$. It means that ST-ISOMAP method have strong anti-jamming in stripe surface defect image dimensionality reduction.

Through the self test of training dataset, we also can obtain a group of more optimization stripe surface defect image dimensionality reduction parameters in ISOMAP method: lower dimensional space is $R^{10}$, Landmark=$200$, embedding neighbor $k=30$. 

(a) 
(b) 
(c) 

Figure 6. Residual variance

Figure 7. The recognition result when the training dataset $M_{432}$ set as the test dataset
Now we set two teams as different test sets, do experiment by using the optimization parameter above, and the detail can be listed as follows:

Team one: Collecting 56 complex stripe surface defect images of the different periods with the M_{56}. These defects are caused by severely abnormal illumination environment, defect images mixed, and the other interference factors. These defects denoted as M_{56}. Part of M_{56} is shown in Fig. 8.

![Stripe surface defect images in M_{56}](image)

Figure 8. Stripe surface defect images in M_{56} (a classified as indentation, it mixed by side indentation and edge crack, and it caused by equipment faults; b classified as hole, it mixed by water and hole; c classified as scar, it is near the stripe edge; d classified as double-skin, it mixed by double-skin and hole)

Team two: Because of the same stage may not including all the defects types, we collect 486 stripe surface defect images of the same periods with the M_{56}. For more close to the real situations, the proportions of each type of stripe surface defect images are the same of the proportion show in Fig. 3. These defects Denoted as M_{486}. In the experiments, training dataset is M_{432}, test datasets are M_{56} and M_{486}. Some well-established dimensionality reduction method including PCA, LPP, and extraction of lower property of image feature are compared by ISOMAP and ST-ISOMAP dimensionality reduction method. Classification methods including k-NN, Decision Tree C4.5 and SVM are compared. These classification correlative parameters are followings: the k of C4.5 is 2; the k=1,2 or 5 in k-NN; the SVM is ploySvm, and degree=5.

However, compute cannot accomplish PCA for 33432 dimensionality reduction because 2G memories are overflow. So we suggest that PCA is weak in high dimensionality reduction. The table 1 shows the other experiments results.

All of these experiments result means that:

1. Experiments show that the method combine isometric mapping dimensionality reduction (ST-ISOMAP and ISOMAP) with Incremental Generalized Regression Network is effective and efficient for stripe surface defects; the highest recognition rate of stripe surface defect can reach to 97%, the highest recognition rate of complex stripe surface defect can reach to 74%.
2. The SVM is inapplicable to ST-ISOMAP, because intra-class distance is small extraordinarily in the low-dimensional space. But SVM combine with ISOMAP will bring more accurate result than ST-ISOMAP.
3. Compare ISOMAP, LPP and image lower property extraction with ST-ISOMAP. And ST-ISOMAP is easier to carry out high recognition rate without parameters optimization and choose classification methods. In other words, ST-ISOMAP adapt to the unknown stripe surface images environment.

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V. CONCLUSIONS

To deal with the typical characteristics of the strip surface defect image, such as complex texture, non-uniform image size, variation illumination environment, and inherent non-linear geometry, a new method that combine the ST-ISOMAP dimensionality reduction with Incremental Generalized Regression Network have primarily suggested for stripe surface defects recognition. The conclusions can be listed as follows:

Firstly, ST-ISOMAP does not require a separate manual feature extraction. It not only present non-linear constructs of images data, but also more adapted to high-dimension images dimensionality reduction.

Secondly, IGRNN can effectively deal with incremental images to the same dimension of training samples. For this reasons, this method can apply to supervised learning and stripe surface defects recognition.

Thirdly, for the natural stripe surface defects, the new method not only better than LPP and Lower Property Feature in the complex stripe surface defect images (M_{56}), but also in the real situation (M_{486}). And another important concern is this new method has lower choice of influence on the process of stripe surface defect images recognition.

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Shengfeng Gan: Currently he is a PhD student of China University of Geoscience, Wuhan, China. His major is the Institute of Geophysics & Geomatics. Research interests include the image processing and the image recognition.

He has participated defects recognition research work in the Wuhan Iron and Steel sand surface, and has completed three research projects and creating economic benefits of nearly 3 million

Lin Sun: is a senior engineer of China University of Geoscience, Chinese. He obtained his PhD from the University of Science and Technology Beijing. He chaired more than 6 national and provincial projects. His research interests include Silicon steel technology and equipment, Rolling processing.

Dianhong Wang: is a Professor and Assistant to the President of China University of Geoscience, Chinese. He also is a doctoral supervisor and Communication and information sciences academic leader in Hubei province. He chaired more than 30 national and provincial projects. Wang Dianhong is co-author of more than 70 articles in journals and conferences, including 8 SCI, 17 EI, 18 ISTP. His research interests include intelligent instrument, computer application and the image processing.