Steel Grade Classification Based on Gabor Filters and K-means Clustering

Sungyoung Kim[1], Jaepil Ko[1], Hoonju Chung[2]

{[1]Dept. Computer Engineering, [2]School of Electronic Engineering}, Kumoh National Institute of Techonogy, Daehak-ro 61, Gumi, Gyeongbuk 730-701, Korea
{sykim, nonezero, hjchung}@kumoh.ac.kr

Abstract. Texture classification is a fundamental area in computer vision and plays a role in image segmentation and pattern recognition. In this paper, we classify steel images into five steel grades - austenite, pearlite, martensite, ferrite and mixture of pearlite and ferrite. To represent feature vectors we use Gabor filters. As the size of images is very large, we randomly select several blocks from an image and extract feature vectors for each block instead of the image. Then a few representative features for an image are selected by using K-means clustering. Experimental results show good performance of our method.

Keywords: Texture Classification, Gabor Filter, K-means Clustering, Steel Grade

1 Introduction

Texture classification has a long history in the computer vision field. A wide variety of texture analysis algorithms for texture classification have been developing ranging from using local edge characteristics such as local binary pattern to multi-resolution analysis such as Gabor filter. Texture analysis plays a key role in image segmentation, image retrieval, pattern recognition, etc.

Several famous techniques for texture analysis have been proposed in the past two decades. Local binary pattern (LBP) [1], scale invariant feature transform (SIFT) [2], histograms of oriented gradients (HOG) [3] and Haar-like feature [4] are used in the fields of objection recognition and detection such as face recognition and human detection. Also, performance of these techniques is excellent. However, they are mainly based on the characteristics of the local area analysis and so do not reflect the global characteristics of the textures. For effective texture classification, it is needed to consider both local and global characteristics of textures.

In this paper, we use Gabor filter for feature representation in the steel grade classification, which can provide a multi-resolution analysis of the steel images. Daugman[5] discovered that the Gabor functions could reflect the characteristics of human visual system. After that, Gabor filter has been used for the texture segmentation or texture classification.

Gabor filters extract the texture feature based on the texture analysis in frequency domain and use multiple filter banks. Due to the nature of the Gabor filter, the processing time to extract feature vectors increase exponentially with the size of image. To speed up the processing time, it is possible to resize input images to smaller size but it can also degrade the performance of extracted features. In this paper, we randomly select several blocks from an image and extract feature vectors for each block instead of the image. We fix the size and the numbers of blocks. As there are so many feature vectors per an image, we compute a few representative vectors by using K-means clustering. In classification step, we use k-NN classifier.

2 Texture Feature for Steel Grade

2.1 Gabor Filter

Two dimensional Gabor function is used for an image. A two-dimensional Gabor function in the spatial domain is given as in Eq. (1). u_0 and φ are the frequency and phase of the function along the horizontal axis and σ_x and σ_y are the space constants of the function along the horizontal and vertical axis, respectively.

$$h(x,y) = \exp\left\{-\frac{1}{2}\left[\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right]\right\}\cos(2\pi u_0 x+\varphi) \quad \textbf{(1)}$$

The Fourier transform of the two-dimensional Gabor function is given as in Eq. (2) and is real-valued with φ=0, σ_u=1/2$\pi\sigma_x$, σ_v=1/2$\pi\sigma_y$ and A=2$\pi\sigma_x\sigma_y$. We can separate specific frequency components of the input image in frequency domain by adjusting the filter parameters. Refer to ref. [6] for Gabor filter and derivation of parameters.

$$H(u,v) = \mathrm{A}\left(\exp\left\{-\frac{1}{2}\left[\frac{(u-u_0)^2}{\sigma_u^2}+\frac{v^2}{\sigma_v^2}\right]\right\}+\exp\left\{-\frac{1}{2}\left[\frac{(u+u_0)^2}{\sigma_u^2}+\frac{v^2}{\sigma_v^2}\right]\right\}\right) \quad \textbf{(2)}$$

2.2 Feature Extraction and Representation

Gabor filter of an image $I(x, y)$ is defined as in Eq.(4) where * indicate the complex conjugate. For texture representation, we use the mean and the standard deviation of the magnitude of the coefficients in each scale and rotation [6]. The mean μ_{mn} and the standard deviation σ_{mn} can be computed as in Eq.(5).

$$W_{mn}(x,y) = \int I(x_1,y_1)\, H_{mn} * (x-x_1, y-y_1)dx_1dy_1 \quad \textbf{(4)}$$

$$\mu_{mn} = \iint |W_{mn}(x,y)|\, dxdy \quad \textbf{(5)}$$

$$\sigma_{mn} = \sqrt{\iint (|W_{mn}(x,y)| - \mu_{mn})^2 dxdy}$$

A feature vector consists of the mean μ_{mn} and the standard deviation σ_{mn}. For example, when the number of orientation K is 4 and the number of scale S is 3, a feature vector is represented to be

$$f = [\mu_{00}\, \mu_{01}\, \cdots\, \mu_{32}\, \sigma_{00}\, \sigma_{01}\, \cdots\, \sigma_{32}\,]$$

We extract feature vectors for an image from several local blocks instead of an entire image. The blocks are selected randomly. To prevent each block from being overlapped too much we restrict initial locations of the blocks to certain area. We divide an image into five area, left-top, right-top, left-bottom, right-bottom and center, and select blocks from each area (Fig. 1). A size of block needs to be a power of 2.

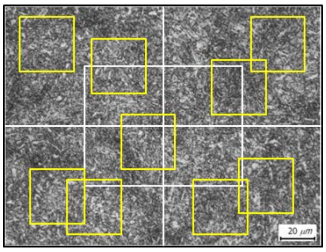
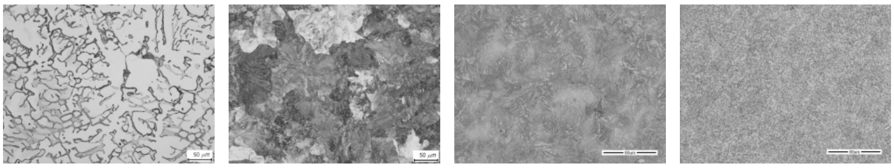


Fig. 1. White rectangles show predefined areas to select blocks that are used to extract features. Yellow rectangles are some examples of the selected blocks randomly.

As there are too many feature vectors in an image we need to reduce the number of the feature vectors. We perform K-means clustering to get a few representative feature vectors for an image. The number of clusters is selected by experiments. In K-means clustering and comparison between two feature vectors, we use the distance defined in ref. [6].

3 Experimental Results

We try to classify images into five texture categories - austenite, pearlite, martensite, ferrite and mixture of pearlite and ferrite. Austenite is a metal of solid solution of iron and has a face-centered cubic crystalline structure. Pearlite is iron-carbon alloy and is formed by a eutectoid reaction as cooling below about 700℃. Pearlite is a common microstructure occurring in many grades of steels. Martensite is formed in quenching steel which contains a lot of carbon. Martensite is formed by the rapid cooling of austenite in a short time and has the needle-like microstructure. Ferrite is pure iron with a body-centered cubic crystal structure. Some examples are shown in Fig. 2.



(a) (b) (c) (d)

Fig. 2. Some examples of steel grade: (a) austenite (b) pearlite (c) martensite (d) ferrite

Table 1 shows the classification results. We select fifteen random blocks and then two representative feature vector in training step. For Gabor filter, we use four scales *S*=4 and six orientations *K*=6. In test, we just use nine random blocks per a test image to speed up comparison. For each block, distance between its vector and all vectors in database is computed. The image is classified into a class with minimum distance (1-NN).

Table 1. Evaluation of the classification result (Class 1: martensite, Class 2: austenite, Class3: pearlite, Class 4: mixture and Class 5: ferrite)

		predict				
		1	2	3	4	5
known	1	40	0	0	0	0
	2	0	3	0	0	0
	3	0	0	2	2	0
	4	0	0	0	40	0
	5	1	0	0	0	13

References

1. Ojala, T., Pietikainen, M.: A Comparative Study of Texture Measures with Classification based on Feature Distributions. Pattern Recognition, Vol. 29, pp. 51–59 (1996)
2. Lowe, D.G.: Object recognition from local scale-invariant features. Proceedings of the Int’l Conf. on Computer Vision, pp. 1150–1157 (1999)
3. Dalal, N., Triggs, B.: Histograms of Oriented Gradients for Human Detection. IEEE Conf. Computer Vision and Pattern Recognition, pp. 886–893 (2005)
4. Viola, P., Jones, M.: Robust Real-time Face Detection. Int. J. Computer Vision, vol. 57, no. 2, pp. 137–154 (2004)
5. Daugman, J.G.: Uncertainty relation for resolution in space, spatial frequency, and orientation optimized by two-dimensional visual cortical filters. Journal of the Optical Society of America A, 2(7), pp. 1160–1169 (1985)
6. Manjunath, B.S., Ma, W.Y.: Texture Features for Browsing and Retrieval of Image Data. IEEE. Trans. PAMI, vol. 18, no. 8, pp. 837–842 (1996)