S5–04

Defect Detection Method by Hybrid PSO–GSA and Gabor Filter

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Summary

Fabric defect inspection is aimed to detect the defect in fabric surface with high accuracy. Real time defect detection is very challenging problem in industrial products.

But visual inspection is very difficult problems because of complexity of fabric patterns and variety of defects. In this paper, new method to detect the defect in fabric surface with optimized EGF (Ellipse Gabor Filter) was proposed. The parameters of EGF are optimized by a novel hybrid PSO–GSA method. A novel hybrid PSO–GSA method was known as excellent method to optimize the models. Computation load is not large because proposed method was used only one optimal filter. The test results obtained exhibit accurate defect detection with low false alarms and show the effectiveness and robustness.

Keywords: Texture; defect detection; Gabor filter;

1. Introduction

Spectral methods such as wavelet transform and Gabor filters are the most widely adopted in defect detection methods. As the wavelet transform [1, 2] posses only limited number of orientation characteristics, Gabor filter has been more reasonable for surface material analysis. Gabor filter are applied to object detection [3, 4], face detection [3] and image noise immunity. Gabor wavelet network (GWN) was deployed by Mak and Peng [9] as the main technique to extract texture features from texture materials. Principal Component Analysis was applied to reduce the dimension of feature vectors in [10~12]. The selection of optimal filter parameters with human was conducted [5] and efficient method to get the parameters automatically proposed in [6~8].

In this paper, a novel model to detect defects in textures with optimal ellipse Gabor filter is proposed. The parameters of ellipse Gabor filter are optimized by using a hybrid particle swarm optimization–gravitational search algorithm (PSO–GSA). Statistical hypothesis test is adopted to detect defect in filtered image. In Section 2, the definition of optimized EGF is described in detail and in section 3, the algorithm and scheme of designing of EGF are described. Section 4 demonstrates the experimental results for a variety of textured–surfaces. In Section 5, the discussion and conclusions in this research are provided.

2. Definition of Elliptical Gabor filter

EGF is the filter with specific bandwidth and orientation which can be centered at any position in the spatial–frequency. Therefore, it is very useful for defect inspection in fabric surface with the help of features which were got by convoluting EGF and image. In [13], the study for defect inspection in fabric texture with EGF was conducted.

The elliptical Gabor filter is defined as follows:

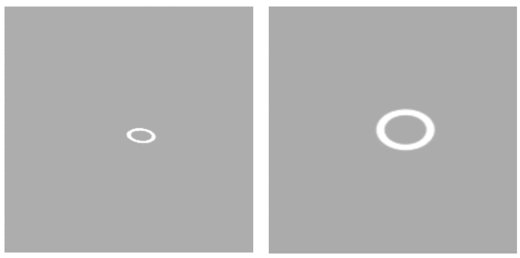
$$G(x,\ y) = g(x',\ y')\exp\left(i2\pi\left(F_0\sqrt{x^2+\frac{y^2}{\gamma^2}}+u_{0x}+v_{0y}\right)\right) \tag{1}$$

where F_0 is the spatial central frequency of the filter in the spatial frequency domain, and $\gamma = \frac{\delta_y}{\delta_x}$ is the aspect ratio of the Gaussian. The 2–D Fourier transform of the EGF in Eq. (1) is given by

$$\widehat{G}(u,\ v) = \frac{\sqrt{2\pi}\alpha}{2}\exp\left[-\frac{\left(\sqrt{(u-u_0)'^2+\gamma(v-v_0)'^2}-F_0\right)^2}{2\alpha^2}\right] \tag{2}$$

Where $\alpha = \frac{1}{2\pi\delta_y}$

Therefore, an EGF is determined by a set of parameters S={u_0, v_0, α, γ, F_0, θ}.



a) b)

Figure 1. An example of an EGF presented in the spatial–frequency domain a) shifted to (0.5, 0.25), b) shifted to (0.5, 0)

Fig. 1 shows an example of Fourier representation of an EGF with parameters (u_0=0.5, v_0=0.25, α=1/9π, γ=4, F_0=0.125, θ=π/3) and (u_0=0.5, v_0=0, α=1/4π, γ=2, F_0=1, θ=0). As shown in Fig. 1 a), the center of the filter is shifted from the coordinate origin to coordinate (0.5, 0.25) and in Fig. 1 b), it is shifted to coordinate (0.5, 0).

3. Defect detection scheme

In this paper, defect detection scheme consists of two steps. First step is training one and second step is detection one.

In training step, optimal EGF to match with fabric features of non–defect texture images is designed. The designing the optimal parameters of EGF is conducted by a novel hybrid PSO–GSA method.

In inspection step, the Gabor filter is designed with parameters optimized in training step and is convoluted with every template images. The proposed defect detection scheme is shown in Fig. 2.

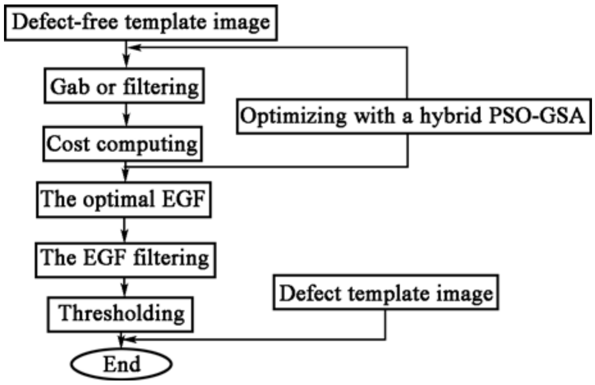


Figure 2. Defect detection scheme

3.2 The cost function

The cost function, which is minimized to design optimal Gabor filters to detect defects is based on Fisher function. Fisher function is applied in some kinds of fields such as pattern recognition and is proofed that is very useful to solve two texture segmentations. In this work, Fisher function is applied as the evaluation function for a novel hybrid PSO–GSA method. Given two texture samples $t_1(x, y)$ and $t_2(x, y)$. The Fisher function is formulated as following to find optimal parameters so that the maximized function value is obtained.

$$F(s) = \frac{(\mu_1 - \mu_2)^2}{\delta_1^2 + \delta_2^2} \tag{3}$$

where (u_1, δ_1) and (u_2, δ_2) are the mean and standard deviations of energy values in the filtered image from t_1 and t_2, respectively. In Eq. (3), every mean and deviation is defined by the set of parameters S. Fisher function is used for defect detection where "unknown" defective textures need to be separated from a "known" defect–free texture background. When template image $f(x, y)$ with size of M×N is given, Fisher cost is the function of the set of Gabor function S and is defined as

$$F(S,\ T) = -\left(\frac{\mu^{S,\ T}}{\delta^{S,\ T}}\right)^2 \tag{4}$$

where the mean $\mu^{S,\ T}$ and standard deviation $\delta^{S,\ T}$ are defined in terms of the $P\times Q$ feature matrix $C^{S,\ T} = [C_{i,\ j}^{S,\ T}]$.

$$C^{S,\ T} = T(x,\ y)\times G(x,\ y) \tag{5}$$

$$\mu^{S,\ T} = \frac{1}{PQ}\Sigma_{i=1}^{P}\Sigma_{j=1}^{Q}C_{i,\ j}^{S,\ T} \tag{6}$$

$$(\delta^{S,\ T})^2 = \frac{1}{PQ}\Sigma_{i=1}^{P}\Sigma_{j=1}^{Q}\left(C_{i,\ j}^{S,\ T} - \mu^{S,\ T}\right)^2 \tag{7}$$

When Fisher cost function is minimum, a set of parameter S^* reflect the texture features mostly and EGF is designed with it's parameters.

4. Optimizing Algorithm

A hybrid PSO–GSA approach is an integrated approach between PSO and GSA which combines the ability of social thinking (*gbest*) in PSO with the local search capability of GSA. In order to combine these algorithms, the updated velocity of agent *i* can be calculated as follows:

$$V_i(t+1) = w\cdot V_i(t) + c_1\cdot rand_i\cdot a_i(t) + c_2\cdot rand_i\cdot(gbest - X_i(t)) \tag{8}$$

where $V_i(t)$ is the velocity of agent i at iteration t, c_i is a weighting factor, w is a weighting function, *rand* is a random number between 0 and 1, $a_i(t)$ is the acceleration of agent i at iteration t, and *gbest* is the best solution so far.

The position of the particles at each iteration updated as follow:

$$X_i(t+1) = X_i(t) + V_i(t) \tag{9}$$

The process of the proposed PSO–GSA algorithm can be summarized as the following steps:

Step 1: Get the data for the system,

Step 2: Generate initial population,

Step 3: Fitness evaluation of agents,

Step 4: Update $G(t)$ and $gbest(t)$,

Step 5: Calculation of the mass of the object, gravitational constant, the total force, and acceleration,

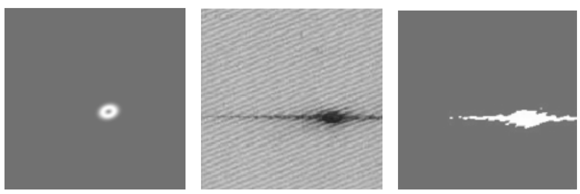
Step 6: Updating agents' velocity and position,

Step 7: Repeat step 3 to step 6 until the stop criteria is reached,

Step 8: Stop.

5. Analysis of the results

We used the texture samples of TILDA database to evaluate the proposed model. The samples in the database contain many kind of textures such as textures fabric, wool weave, leather and sandpaper and different types of defects. As experimental data, 30 defective textures and 60 non–defective textures were used and texture images are 512×512 (8 bit grey level range). Every non–defective images were used in training step and optimized filter parameters were got. The optimized parameters were used to design the filter and designed filter was used to filter the defective sample images in frequency domain. Fig. 3 shows the results of defect detection using optimal filter for soiled end detects. The optimal parameters are got with a hybrid PSO–GSA algorithm in training step and the figure of EGF with optimal parameters is shown in Fig. 3 a). Defect image is passed the optimal EGF that is got in training step and filtered image becomes binary image by thresholding.



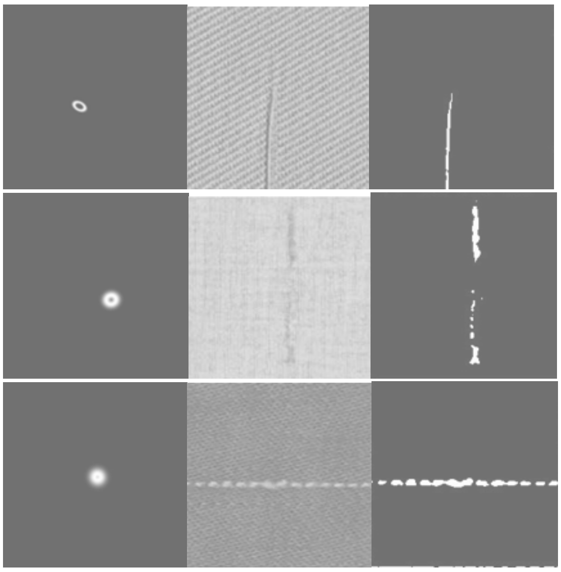
a) b) c)

Figure 3. The result of defect detection with EGF

a) Image of EGF, b) Orignal Image, c) Result Image

The result binary image is shown in Fig. 3 c). As shown in figure, the TPR and FPR are excellent.

Fig. 4 shows the defect detection result of texture images with a variety of defect shapes such as overshot, gout and foreign fiber.



a) b) c)

Figure 4. The result of defect detection in texture with overshot
a) Image of EGF, b) Orignal Image, c) Result Image

Table 1. Statistics for the detect detection results

method	Input type	Results	
		True detection	False detection
EGF	Defective	59	1
	Defect−free	30	0

Table 2. Percent efficiency of the proposed method

Detection details	Efficiency, %
TPR	98.97
FPR	0
ACC	99.5

Tables 1 and 2 summarize the efficiency of model, where TPR (True Positive Rate) refers to detection of defect image correctly, FPR (False Positive Rate) refers to detection of non−defect images as defection images, and ACC denotes accuracy. It can be observed that the TPR and ACC obtained from the optimal EGF are excellent.

6. Conclusion

We presented a novel defect detection method in uniform and structured fabrics with EGF and a hybrid PSO−GSA algorithm. The EGF has the excellent in the spatial−frequency domain than typical Gabor Filter and was used to extract the feature of textures. A hybrid PSO−GSA algorithm was used to design the optimized EGF in training step. To evaluate the proposed model, images of the TILDA Textile Texture Database were used and compared against ground−truth results obtained using a number of human observers. The proposed detection model achieved the TPR of 98.97%, FPR of 0% and ACC of 99.5%. The result of this experimental evaluation shows that the proposed model is very efficient and effective.

References

1. Heidari N., Azmi R., Pishgoo B., 2011, Fabric textile defect detection, by selecting a suitable subset of wavelet coefficients, through genetic algorithm, *Int. J. Image Process.* 5(1) 25−35.
2. Tsai D. M., Chiang C. H., 2003, Automatic band selection for wavelet reconstructions in the application of detect detection, *Image Vis. Comput.* 21, 413−431.
3. Shen L., Bai L., Fairhurst M., 2007, Gabor wavelets and general discriminant analysis for face identification and verification, *Image Vision Comput.* 25(5) 553−563.
4. Kamarainen, Kyrki V, Kalviainen H, 2002, Fundamental frequency Gabor filters for object recognition, in: *Proc. of 16th International Conference on Pattern Recognition* 1 628−631.
5. Dunn D., Higgins W. E., 1995, Optimal Gabor filters for texture segmentation, *IEEE Trans. Image Process.* 4 947−964.
6. Bodnarova A., Bennamoun M., Latham S., 2002, Optimal Gabor filters for textile flaw detection, *Pattern Recognit.* 35 2 973−2 991.
7. Liu H., Han J., 2006. Defect Detection in Textiles Using Optimal Gabor Wavelet Filter, presented at *the Proceedings of the 6th World Congress on Intelligent Control and Automation.*
8. Mak K. L., Peng P., 2004. Detecting defects in textile fabrics with optimal gabor filters, *Int. J. Appi. Sci. Eng. Technol.* 1 274−282.
9. Bissi L., Baruffa G., Placidi P., Ricci E., 2013, Automated defect detection in uniform and structured fabrics using Gabor filters and PCA, J. *Vis. Commun. Image Represent.* 24 838−845.
10. Mak K. L., Peng P., Yiu K. F. C., Fabric defect detection using morphological filters
11. Holland J. H., 1975. Adaptation in Natural and Artificial Systems, *The University of Michigan Pres*s, Ann Arbor.
12. Zhang Y. F., Sun N. L., Gao Y., Cao M. Y., 2008. A new eye location method based on Ring Gabor Filter, presented at *the Proceedings of the IEEE International Conference on* 28. *Automation and Logistics.*