

# Identifying city PV roof resource based on Gabor filter

**Xu Ruhang<sup>1\*</sup>, Liu Zhilin<sup>2</sup>, Huang Yong<sup>3</sup>, Zhang Xiaoyu<sup>4</sup>**

<sup>1</sup>School of Economics and Management, North China Electric Power University, Beijing, China

<sup>2</sup>National Institute of Clean and Low Carbon Energy, Beijing, China

<sup>3</sup>China Nuclear Engineering& Construction Corporation, Beijing, China

<sup>4</sup>State Grid Jibei Electric Power Company Limited Management Training Center, Beijing, China

\*Corresponding author: sdxu8888@foxmail.com

**Abstract.** To identify a city's PV roof resources, the area and ownership distribution of residential buildings in an urban district should be assessed. To achieve this assessment, remote sensing data analysing is a promising approach. Urban building roof area estimation is a major topic for remote sensing image information extraction. There are normally three ways to solve this problem. The first way is pixel-based analysis, which is based on mathematical morphology or statistical methods; the second way is object-based analysis, which is able to combine semantic information and expert knowledge; the third way is signal-processing view method. This paper presented a Gabor filter based method. This result shows that the method is fast and with proper accuracy.

## 1 Introduction

Urban building roof area estimation is a major topic for remote sensing image information extraction. Jesus and Jean [1] try to reduce an image of spots into a table with a measure of the intensity for each spot in DNA microarray images analysis, which is based on mathematical morphology methods. Martino [2] proposed a multiscale segmentation method based on mathematical morphology approaches for remote sensing image segmentation. Isabelle and Henri [3] proposed some ways to build a fuzzy mathematical morphology for spatial information processing.

Object based image analysis (OBIA) became a heat in image feature extraction in early 2000s. OBIA mainly combined expert knowledge and semantic information in a multi-scale image processing workflow, which can generate somewhat more precise feature extraction result. Its emergence has nevertheless provided a new, critical bridge between the spatial concepts applied in multiscale landscape analysis [4]. It should be clearly stated that much of the work referred to as OBIA originated around the software known as "eCognition". Ursula et al. [5] built a fuzzy combined workflow in eCognition to extract objects by the forest mapping management. Kabir et [6] al. calculated the 'bright' roof area in Dhaka with OBIA approaches, and claiming to achieve an accuracy rate as high as 97.6%. Similar research are as shown in [7,8]. What's more, OBIA approach is still based on region growing methods. The accuracy rate may be affected when the target has similar patterns with the background. This situation is obvious in most urban area of China. Most of the buildings in this area have concrete appearances, which may be confounded with the background roads.



John [9] introduced an image compressing and analysis method by discrete 2-D Gabor transforms. Anil and Farshid [10] present a texture segmentation algorithm by a multi-channel filtering process which is based on a bank of Gabor filters. Wanga et al. [11] pointed out that when it comes to image denoising, Gabor feature based nonlocal means filter are more robust. Gabor-based texture features were used to measure the self-similarity. Gabor filter are also widely used in other kind of texture extraction analysis context [12]. Because most of urban residential buildings are with textures and patterns, signal processing method may be an easier and faster way to acquire roof-top data. According to IEA method, the building façade area can be briefly estimated based on related roof area and building type [13].

## 2 Roof recognition based on Gabor filter

To avoid the complex calculation of OBIA methods and avoid using eCognition, this paper developed a maybe less accurate but simpler and faster way to recognize roof-tops.

The remote sensing results are normally digital images, which can be treated as spatial domain signals. 2D Gabor filter is particularly appropriate for texture representation and discrimination because its frequency and orientation representation are similar to those of human visual system in image processing. The Gabor filter used in this paper can be described in Equation (1).

$$gabor = \exp\left(-\pi \cdot \left(\frac{x_\theta}{\delta_x}\right)^2 + \left(\frac{y_\theta}{\delta_y}\right)^2\right) \cdot \cos(2\pi f_0 x_\theta) \quad (1)$$

$gabor$  is the Gabor filter.  $\delta_x$  and  $\delta_y$  are the standard deviations for x-direction and y-direction filter value.  $f_0$  is the center frequency of the filter.  $x_\theta$  and  $y_\theta$  are the rotated coordinates with angle  $\theta$ , which can be described in Equation (2) and (3).

$$x_\theta = \cos \theta \cdot x + \sin \theta \cdot y \quad (2)$$

$$y_\theta = -\sin \theta \cdot x + \cos \theta \cdot y \quad (3)$$

$x$  and  $y$  are the original coordinates.

A typical Gabor filter is as shown in Figure 1. The frequency domain of 4 different-orientation Gabor filters is as shown in Figure 2. After a convolution of Gabor filter and the original image, the information near the center frequency is retained, and other parts are filtered.

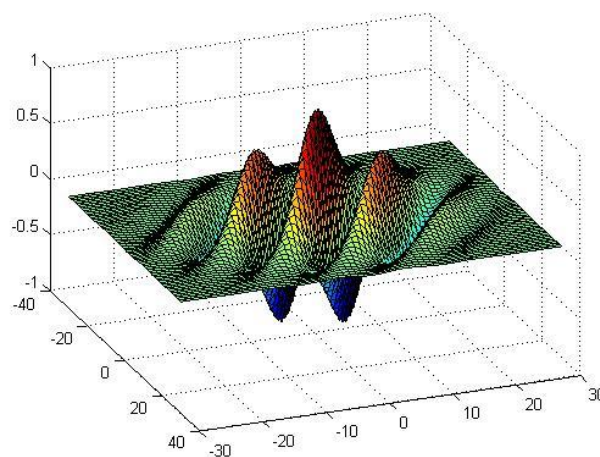


Figure 1: A typical Gabor filter

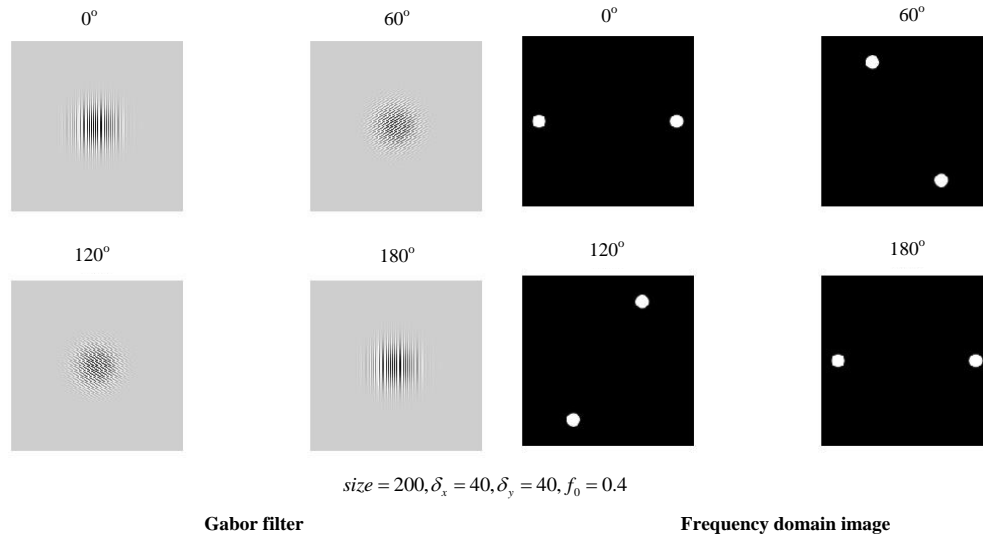


Figure 2: The frequency domain of 4 different-orientation Gabor filters

Most of the residential roof-top textures are with regularity and have a center frequency. This paper uses a window function to cut out a piece of center-frequency signal. The cut should be along the direction which has the best pattern repeatability. The cut direction is as shown in Figure 3. The window function is as shown in Equation (4).

$$g_a(x) = \frac{1}{2\sqrt{\pi a}} e^{-\frac{x^2}{4a}}, a > 0 \quad (4).$$

The Fourier transformation of this center-frequency signal has an obvious peak which is not near the direct current center. This peak frequency can be treated as the center frequency of the roof-top texture, because the repeatability of the patterns is obvious. In fact, this center frequency is in the low frequency part of the signal, and it gives the appropriate position of the roof-tops. For example, in the remote sensing image in Figure 3, the roof-top texture is of great regularity. The white line in the picture holds the position of the cut-out signal. The Fourier transformation of this signal is as shown in Figure 4, and the center frequency of the texture is obvious. Based on this sampling, the parameter  $f_0$  and  $\theta$  of the Gabor filter can be acquired.  $\delta_x$  and  $\delta_y$  should be based on the image resolution and the relative size of the roof-top area, this process can be carried out by a simple test. With the parameter value  $f_0 = 18$ ,  $\theta = 1.51$  and  $\delta_x = \delta_y = 12$ , the filtered result is as shown in Figure 4. Next, this image should be processed with binarization algorithm with proper threshold, which is acquired by test. The binarized result is as shown in Figure 5 with threshold=0.6. The result in Figure 5 gives the low-frequency information of the roof-tops.



Figure 3: Window function cut in the remote sensing image

In Figure 5 white parts are referred as “Gabor patches”. Among these patches, some of them hold potential roof-top area, and they are referred as “roof-top patches”, but some of them are other land surface objects whose textures happen to have similar frequency with our target roof-top. To solve this problem, this paper developed a method, which can be referred as “shadow reflection”. As can be seen in Figure 3, the shadows have clear boundaries with other parts of the image, and because the brightness of the objects within the shadows is far lower than other parts of image, the shadow areas can be treated as very smooth areas, which mean the gradients of the pixels within the shadow areas are relatively very small. Based on this property, the shadow parts can be extracted.

To start, the gradients of each pixel should be calculated. This paper uses Sober operator. To synthesize the gradients of x-direction and y-direction, the gradients of each pixel is calculated as in Equation (5).

$$g = \sqrt{gx^2 + gy^2} \quad (5)$$

$gx$  is x-direction gradients and  $gy$  is y-direction gradients. The gradients distribution of image in Figure 2 is shown in Figure 6. From Figure 6 we can see that gradients within shadows are significantly smaller than other parts of the image. To make more clear shadow edges, Canny edge detector is applied. The Canny-detected result is shown in Figure 7. It can be seen that the edge of each shadow is acceptably detected. Next process can be described with the following pseudo codes.

```
threshold(gradient, t);
overlap = gradient & edge;
overlap = imopen(overlap, o);
overlap = imclose(overlap, o);
result = imcut(overlap, a);
```

*gradient* is the gradient result, and *edge* is the edge detection result. Function *threshold* makes each pixel whose gradient value is under threshold  $t$  in *gradient* value 1. & represents an “and” operation. Function *imopen* carry’s a *mathematical morphology* open operation with mask *o* to cut off any small connected parts. Function *imclose* carries a *mathematical morphology* close operation with mask *o* to fulfill any possible holes in potential patches. Function *imcut* cut out the patches whose area size is smaller than threshold  $a$  in the result. The result of this process is shown in Figure 8, in which the shadow patches are clear. The next step is called “shadow reflection”, it is a two-way confirmation process. The basic idea is to use shadow patches to confirm a related Gabor patch, to make it a roof patch. And to make a fitting of the roof-tops, both-way information should be combined. This paper mainly makes rectangle fitting of the roof-top area. This process can be described with the following pseudo codes.

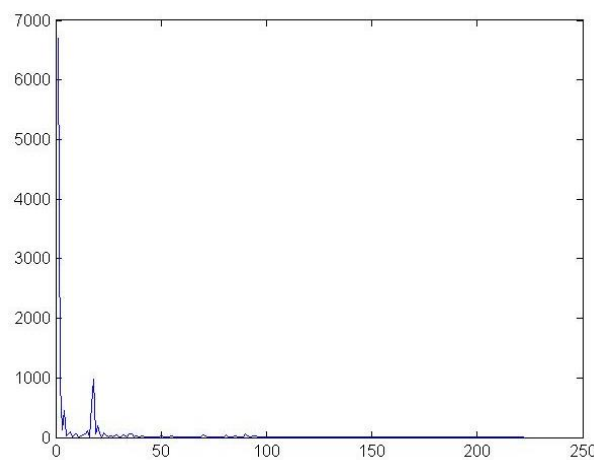


Figure 4. The Fourier transformation of the sampling signal

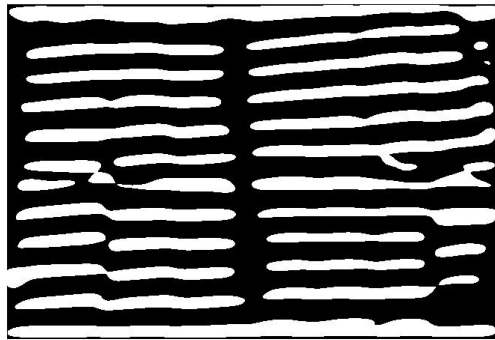


Figure 5: The binarized result

```
edge=getedge(shadow);
ledge=getledge(edge);
line=linefit(ledge);
overlapdec=ovlpdec(line,gabor,l);
roofpat=confirroof(overlapdec);
result=fitting(roofpat,line);
```

Each function processes with a static parameter *Angle*, which is the angle between the sunlight and x-axis. *shadow* is shadow patches, *gabor* is Gabor patches. Function *ledge* gets the next-to-roof edge of shadow patches depending on *Angle*. Function *linefit* get the line fitting result of the *ledge*. Function *ovlpdec* get the overlap result if the *ledge* move to gabor patches with *l* distance. Function *confirroof* decide which gabor patch is roof patch depending on the *overlapdec* value. Function *fitting* makes a rectangle fitting for every roof patch based on shadow information and Gabor patch information.

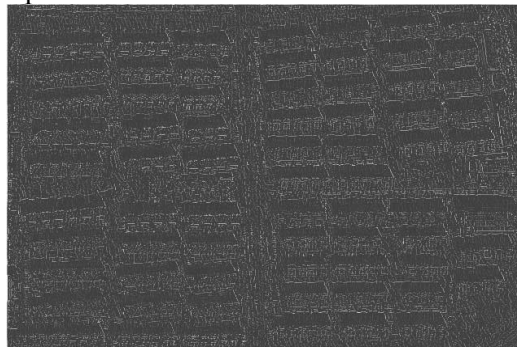


Figure 6: The gradients distribution

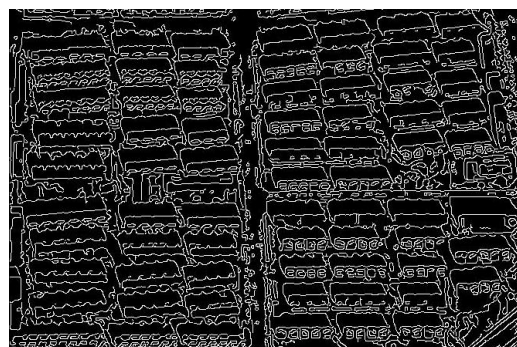


Figure 7: The Canny-detected result



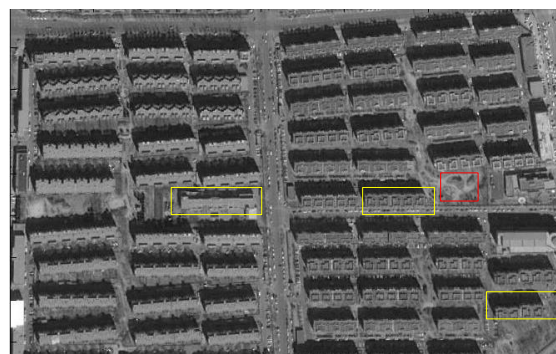


Figure 8: The shadow patches

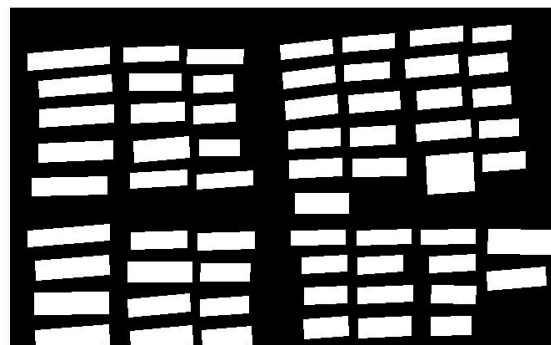
### 3 Application Case

The method is carried out on a residential zone of Beijing. By comparing the automation recognition results with manual recognition results in some tests for a certain urban district, it is able to evaluate the accuracy of this process. From Figure 9 we can see the errors. The comparison result is as shown in Table 1. The obvious area recognition result is marked by red rectangle in Figure 9. The main reason for this kind of mistake is that some ground objects have similar frequency with the target roof-tops, and at the same time they are near the shadows. The missing targets are marked by yellow rectangles in Figure 9. The main reason for this kind of mistake is that the shadows of these targets are not evident enough compared with other targets. It should be noted that some buildings are not deemed as targets in the example recognition process because the main frequency is not adopted. The main frequency should be sampled if these buildings are to be recognized.

It must be pointed out that different countries may have different building patterns, so for different urban areas in different countries this evaluation must be carried out separately considering the patterns.



(a) Original Image



(b) Roof-top recognition result

Figure 9: The processing result

Table 1: The recognition result comparison

	Manual recognition result	Automation recognition result
Recognized target number	75	72
Obvious area mistake	-	1
Missing target	-	3
Area mistake rate	-	1.39%
Missing target rate	-	4.17%

#### 4 Conclusion

This paper worked out a method to estimate the restriction brought by the roof resource in a certain location. Compared with the OBIA method which is usually coupled with an software known as eCognition, this paper provide an approach which is based on signal processing method and the geographical characteristics of the residential buildings to estimate the roofs. The result shows that this approach has acceptable error rate, and is efficient enough for the estimation task.

#### References

- [1] Jes'us Angulo , Jean Serra. Automatic analysis of DNA microarray images using mathematical morphology[J]. Bioinformatics 2003;19(5):553-562.
- [2] Martino Pesaresi, Jon Atli Benediktsson. A New Approach for the Morphological Segmentation of High-Resolution Satellite Imagery[J]. Transactions on the geoscience and remote sensing 2001;39(2):309-320.
- [3] Isabelle Bloch, Henri Maitre. Fuzzy mathematical morphologies: A comparative study [J]. Pattern Recognition 1995;28(9):1341-1387.
- [4] Jon Atli Benediktsson. Classification and Feature Extraction for Remote Sensing Images From Urban Areas Based on Morphological Transformations [J]. IEEE transactions on geoscience and remote sensing 2003;41(9):1940-1949.
- [5] Ursula C. Benz, Peter Hofmann, Gregor Willhauck, Iris Lingenfelder, Markus Heynen. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information [J]. ISPRS Journal of Photogrammetry and Remote Sensing 2004;58(3-4):239-258.
- [6] Md. Humayun Kabir, Wilfried Endlicher, Jonas Jägermeyr. Calculation of bright roof-tops for solar PV applications in Dhaka Megacity, Bangladesh [J]. Renewable Energy 2010;35(8):1760-1764.
- [7] Hay, G.J., Castilla, G., Wulder, M.A., Ruiz, J.R.. An automated object-based approach for the multiscale image segmentation of forest scenes [J]. International Journal of Applied Earth Observation and Geoinformation 2005;7 (4):339-359.
- [8] T. Santosa, N. Gomesb, S. Freirea, M.C. Britoc, L. Santosb, J.A. Tenedório. Applications of solar mapping in the urban environment [J]. Applied Geography 2014;51:48-57.
- [9] John G. Daugman. Complete discrete 2-D Gabor transforms by neural networks for image analysis and compression [J]. IEEE transactions on acoustics, speech, and signal processing 1988;36(7):1169-1179.
- [10] Anli K. Jain, Farshid Farrokhnia. Unsupervised texture segmentation using Gabor filters [C]. Systems, Man and Cybernetics, 1990. Conference Proceedings 1990:14-19.
- [11] Shanshan Wanga, Yong Xiab, Qiegen Liua, Jianhua Luoa, Yuemin Zhue, David Dagan Feng. Gabor feature based nonlocal means filter for textured image denoising [J]. Journal of Visual Communication and Image Representation 2012;23(7):1008-1018
- [12] Jun-Bao Li. Gabor filter based optical image recognition using Fractional Power Polynomial model based common discriminant locality preserving projection with kernels [J]. Optics and Lasers in Engineering 2012;50(9):1281-1286.
- [13] IEA. Potential for building integrated photovoltaics. Report IEA 2002