Bridge recognition of median-resolution SAR images using pun histogram entropy

Wenyu Wu (吴文宇)*, Dong Yin (尹 东), Rong Zhang (张 荣), Yan Liu (刘 岩), and Jia Pan (潘 嘉)

Institute of Image Processing and Remote Sensing, University of Science and Technology of China, Hefei 230027, China

**E-mail: wenyuwu@mail.ustc.edu.cn*

Received August 13, 2008

A novel algorithm for bridge recognition of median synthetic aperture radar (SAR) images using histogram entropy presented by Pun is proposed. Firstly, Lee filter and histogram proportion are used to denoise the original image and to make the target evident. Then, water regions are gained through histogram segmentation and the contours of water regions are extracted. After these, the potential bridge targets are obtained based on the space relativity between bridges and water regions using improved contour search. At last, bridges are recognized by extracting the feature of Pun histogram entropy (PHE) of these potential bridge targets. Experimental results show the good qualities of the algorithm, such as fast speed, high rate of recognition, and low rate of false target.

OCIS codes: 100.0100, 100.3008, 280.6730.

doi: 10.3788/COL20090707.0572.

Synthetic aperture radar (SAR) has been widely applied to gain large-area and high-resolution images in aerospace, ground reconnaissance, remote sensing or resource census, etc. Target recognition in SAR image has been one of the hotspots in the development of remote sensing. Bridge recognition is one important kind of SAR image target recognition, as the recognition is very useful for image registration, precision-guidance, map drawing, target detection, and so on.

Bridge targets have some distinct features in median-resolution SAR images, such as the high gray value, the limited length and width, the usually constant width, the changeless direction, the approximately straight line edges, and water regions which have constantly low gray value are usually besides them, etc. By now, the ways for SAR image bridge recognition are classified into three aspects. One is based on amalgamation between SAR images and optical images[1−8], which synthesizes the information of each kind of images to recognize the targets. Another is based on morphological method[2], which makes water regions connected and recognizes the targets in these connected regions. The third one is based on edge information extraction[3−9], which detects the contours in the images and gains the result using the features of target contours, such as parallel edges. The first aspect needs different kinds of images of one region, which is hard to realize, although it has high precision. The second aspect cannot be automatic, for the morphological disposals are not the same in different images. The third aspect can cause high rate of false target, for the edges in SAR images are rugged and the noise has severe interference. Even more, sometimes the edges are not parallel in median-resolution SAR images. In this letter, using space relativity between bridges and water regions and the feature of Pun histogram entropy (PHE)[6], we propose a novel algorithm for bridge recognition of median-resolution SAR images, in which we use the feature of PHE instead of sharp features to make sure that the target can be recognized even if its shape is distorted by noise.

For the noise in SAR images is usually multiplicative, the difference operator which is used in optical images should not be used here. Instead, there are many other filters to denoise it, such as Lee filter[4], Frost filter, Kuan filter[5], and independent component analysis (ICA)[10], etc. Lee filter[4], which is based on the model of complete-grown multiplicative fleck noise, is used in this letter according to the following consideration. Although the Lee filter results in some fuzzy images, the edge contours of water are preserved and the features of land targets are weakened.

Suppose that transcendent mean and variance can be gained by partial mean and variance, then

$$R = I + (C_u - I) \times W(t), \tag{1}$$

$$W(t) = 1 - C_u^2/C_I^2, \tag{2}$$

where $C_I > C_u$, R is the partial gray value after smoothing process. I, σ_I, and C_u are the mean of partial gray value, the standard variance of image data, and the gray value of the center pixel of the partial area in smoothing model, respectively. C_I is the partial variance parameter of I, $C_I = \sigma_I / I$. Using Eq. (1), the image smoothing is actually performed so that the pre-processed image would be used in the next step.

Sharp features are usually used in bridge recognition of SAR images. Admittedly, sharp features are visual and easily extracted. However, the noise interference and the imaging mechanism give rise to the distortion of target sharps, causing that sharp features are unable to describe the universal characteristics of different bridges in different images. The PHE feature, used in this letter shows the distribution of gray levels and the abundance of information, and almost not changed by sharp distortion. Therefore, it can be widely used in different images.

1671-7694/2009/070572-04

As the Shannon information theory expresses, entropy is the measure of uncertainty. The greater the entropy is, the worse proportioned the system is, and the greater the uncertainty is. Suppose that the random events are denoted as $x(1),\ x(2),\ \ldots,\ x(n)$, whose probabilities are $p(1),\ p(2),\ \ldots,\ p(n)$. If $\forall i \in \{1,\ 2,\ \ldots,\ n\}$, $0 \leq p(i) \leq 1$, $\sum\limits_{i=1}^{n} p(i) = 1$, then the entropy of single random event is

$$H(p(i)) = -p(i)\log p(i) - (1-p(i))\log(1-p(i)). \quad (3)$$

PHE is a kind of entropy measure based on presumptive distribution. Suppose the gray levels of the histogram are ranged in $\{0,\ 1,\ \ldots,\ l-1\}$, then the entropy of every gray level is

$$H = -\sum_{i=0}^{l-1} p(i)\cdot\ln p(i), \quad (4)$$

where $p(i)$ is the probability of level i.

Suppose that there is a threshold t dividing the image into two parts, target region and background region. For the reason that usually the bridge target is whiter than background, we have

$$p_t = \sum_{i=t}^{l-1} p(i). \quad (5)$$

The posterior probabilities of target and background are denoted as $p_{\rm d}$ and $p_{\rm b}$, whose relativity can be expressed as

$$p_{\rm d} = p_t, p_{\rm b} = 1 - p_t. \quad (6)$$

So the posterior entropy of the image, PHE, is gained as

$$H'(t) = -p_t \log p_t - (1-p_t)\log(1-p_t). \quad (7)$$

The relativity between PHE and image gray level can be described as following: the wider range the gray levels spread, the more information the image has, and the greater PHE is. Otherwise, the closer range the gray levels spread, the poorer information the image has, and the less PHE is. Hence PHE can express the distribution of image gray level and the richness of the image information, which obviously cannot be changed greatly by sharp distortion. Considering that the bridge target always has more information than false target and the gray levels spread wider range in bridge target than those in false targets, we can utilize this feature to recognize the bridge target from the potential target region and to remove the false target.

Figure 1 shows the flow of the recognition algorithm. In order to obtain the basic contours of water regions and have a good effect of de-noising, the Lee filter[4] is used firstly to perform pre-filtering on the original SAR image. As the result of the filtering, the edge contours of the water regions are preserved and the land targets are weakened. Also, we use histogram proportion to enhance the feature of the bridge targets. After these pre-processing steps, water regions can be segmented from the image and water contours can be easily extracted, which will reduce the data quantity that needed to be processed. And then, based on the space relativity between bridges and water regions, the potential bridge targets are extracted by applying an improved contour search to calculate the minimum distance of each water region. At last, the bridge targets can be recognized by extracting the feature of PHE of the potential targets in the original SAR image.

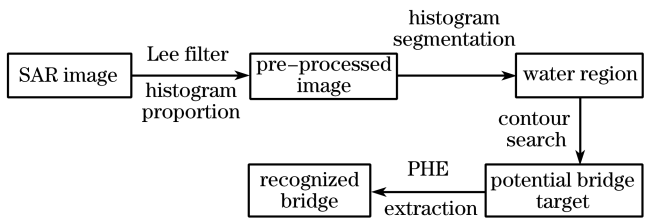


Fig. 1. Flow of bridge recognition algorithm.

After pre-processing, water regions can be obtained by segmentation. Histogram segmentation is proved to be a good method[7]. Usually, the gray value of the first trough in the gray value level histogram can be used as the upper threshold of water, which is noted as $g_{\min}$. Supposing that the histogram is a curve function noted as $h(g)$, where g is the gray value, we can gain $g_{\min}$ by calculating the first minimum of the curve function as

$$\frac{\partial h}{\partial g} = 0, \text{and}\ \frac{\partial^2 h}{\partial^2 g} > 0. \quad (8)$$

The first g who obeys the above formula is $g_{\min}$.

Using $g_{\min}$, we can segmented water regions from the SAR image as

$$g(i,j) = \begin{cases} 255, f(i,j) < g_{\min} \\ 0, f(i,j) \geq g_{\min} \end{cases}, \quad (9)$$

where $f(i,j)$ is the gray value of the image after pre-processing and $g(i,j)$ is the gray value of the segmented image. The water regions will show white while other regions will show black in the image after the segmentation.

The water interference, which we call white hole, exists in the land regions after segmentation, while black holes also exist in water regions. These holes should be removed, or they will influence the following steps. We utilize an effective method to realize it by marking the connected regions. First we mark every 8-connected region, and then calculate the pixels of it. By setting a lower threshold of pixel count, the gray value of the white regions whose pixel counts are below the lower threshold will be set as 0, thus the white holes can be all removed. Also, the black holes in the water region can be removed by using the same method except setting black pixels of black holes as 255. This method (removing white holes) is described as follows.

1) Scan the binary image from left to right, and from underside to upside. Mark every white pixel which has not been marked before. When the whole image has been scanned, go to step 3.

2) From this pixel, scan the 8-neighborhood. If the pixel in 8-neighborhood is also white, set it the same mark as the center pixel. Then turn to step 1.

3) Calculate the pixel count of every region marked. If the count is below the lower threshold, set the gray value

of all these marked pixels 0.

Based on the transcendental knowledge about bridges that a bridge must be located between two water regions, we can search potential bridge targets between water regions which have been extracted through the above steps. Considering the limitation of bridge width, we can set an upper threshold T_r according to the resolution of the image and then calculate the minimum distance between each water region. If the distance is larger than T_r, we should confirm that there are no bridge target in this region. Otherwise, consider it as a potential bridge target. However, it is too complex to use all the pixels in the water regions, as the computational complexity is $O(n^4)$. Contour search is a good method to calculate the minimum distance, whose computational complexity is only $O(n^2)$. Considering the ragged contours of SAR images, we utilized an improved contour search to obtain potential bridge targets. This method is expressed as following:

1) Extract contours by scanning every water region. If a pixel in the region is white while its 8-connected pixels are also white, set it black.

2) Calculate the minimum distance between each contour, denoting it as $T_{\min}$. If $T_{\min} < T_r$, go to step 3. Otherwise, keep on calculating $T_{\min}$.

3) Search the two contours and storing all suited pixels whose distance is less than $1.5T_{\min}$ into two arrays, PBT_array1 and PBT_array2. The two arrays are two suited potential bridge contours. As the contours are ragged in SAR images, it is possible that the contours we gain are intermitted or not all the contours are potential bridge contours, such as riverside contours. We should utilize two lines to replace the two arrays. Suppose the array has n pixels. Then the distance between the line and the pixels can be denoted as $h_1,\ h_2,\ \cdots,\ h_n$. So the line must obey

$$h_1 + h_2 + \cdots + h_n = \min . \qquad (10)$$

The two lines are treated as the potential bridge contours approximately, between which is the potential bridge target.

In the last step, the PHE of the potential bridge target in the original SAR image is extracted as following:

1) According to the gray level histogram of the potential target, calculate the probability of every gray level, denoted as $p(i), i = 0,\ 1,\ \cdots,\ 255$.

2) Using Eq. (5), we can obtain Pun gray

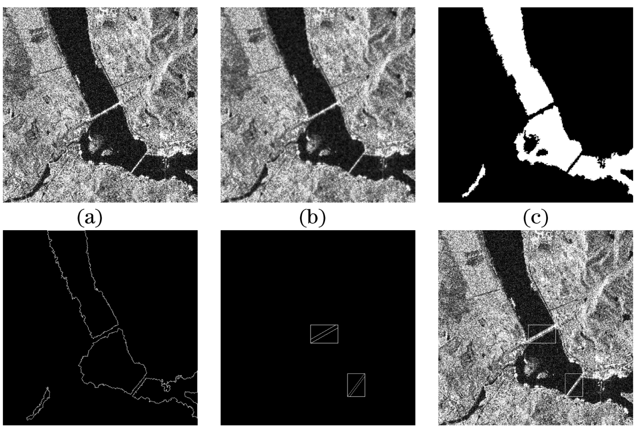


Fig. 2. Bridge recognition using PHE (1).

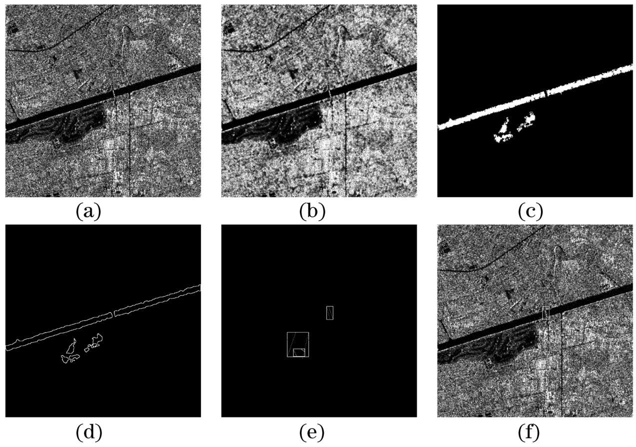


Fig. 3. Bridge recognition using PHE (2).

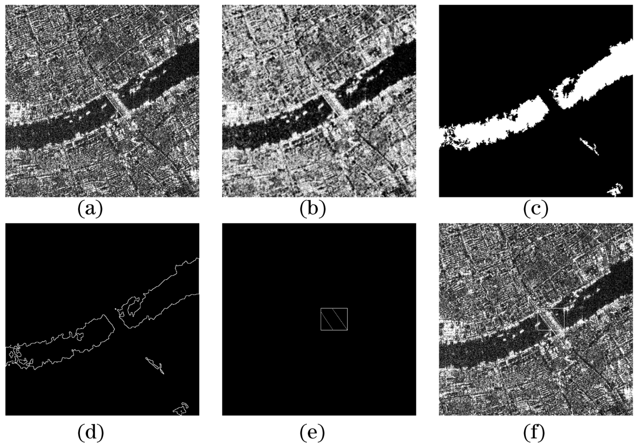


Fig. 4. Bridge recognition using PHE (3).

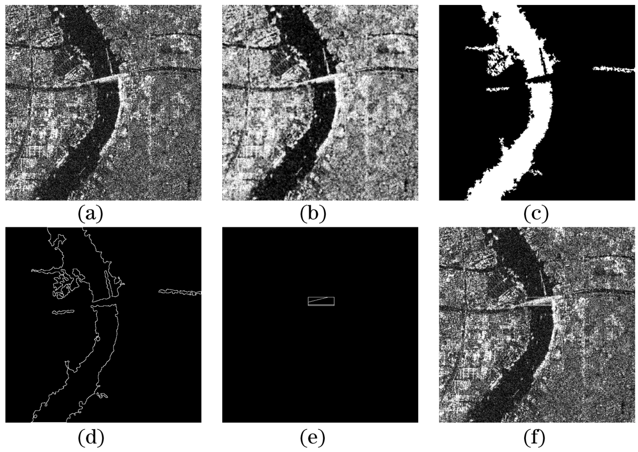


Fig. 5. Bridge recognition using PHE (4).

Table 1. PHE of Potential Targets

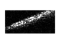
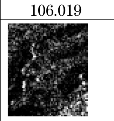
Potential Bridge Target						
PHE	132.348	96.952	102.982	119.312	106.019	123.338
Potential Bridge Target						
PHE	146.556	92.254	64.154	37.736	65.204	19.269

Table 2. Evaluation Using Different Features

Feature	PHE	Parallel Edges	Length-Width Ratio
Rate of Recognition	100%	84.93%	95.89%
Rate of False Target	1.37%	4.11%	10.96%
Time Consumption	3.13 s	3.71 s	3.06 s

distribution probability p_t, where t is from 0 to 255.

3) Based on Eq. (7), the PHE of every p_t can be calculated as $H'(p_t)$.

4) The PHE sum of the potential target H_p can be gained as $H_p = \sum H'(p_t)$.

After standardizing the PHE sum, as the PHE of bridge target is distinctly larger than that of false target, we can easily recognize bridge targets and false targets by setting a threshold of this feature.

This algorithm has been coded in VC++ 6.0, running in a computer with CPU Pentium IV 1.4 GHZ, RAM 256 MB. The experiment chooses 25 images whose resolution is 6.25 m and 25 images whose resolution is 2 m, totally having 73 bridges whose length is larger than 50 m. The sizes of these images are all 512 × 512. The results show that all the bridges are recognized and all the false targets are removed, using 2−4 seconds in average. The whole algorithm is totally automatic. Some results are shown as following.

Figures 2−5 are some results of every step in this algorithm. (a) show the original SAR images. There are bridges, rivers, mountains, and urban zones in the images. (b) show the images after using Lee filter[4] and histogram proportion, the multiplicative speckles are removed and the bridge targets are enhanced, although there are some fuzzy areas. (c) show the results by water segmentation where little white and black holes have been removed. (d) show the extracted contours of the water regions. By utilizing an improved contour search, the potential bridge targets are obtained, shown in (e). (f) are the recognition results by using the feature of PHE. All the bridge targets are shown in white rectangle rims. Especially in Fig. 5, we can clearly see that the sharp of this bridge is clearly distorted as the contours of the bridge are unparallel. This reminds us that it will fail to recognize this bridge target by using sharp features, but it works effectively by using PHE.

Table 1 shows us the PHE of some potential bridge targets, where all the targets except the last four are bridges. From this table we can easily find that PHE of bridge is distinctly different from that of false target. Table 2 shows the results of bridge recognition using PHE and some shape features. In this table, we can see that the recognition using PHE has the highest rate of recognition and a lowest rate of false target, even the time consumptions are almost the same. It means the algorithm using PHE is more efficient than other two methods.

In conclusion, based on the space relativity between bridges and water regions, a novel algorithm is developed to recognize bridges in median-resolution SAR images, using the feature of PHE. The results obtained by this method show the good effects of fast speed, automatic recognition, high rate of recognition, and low rate of false target.

References

1. S. Houzelle and G. Giraudon, in *Proceedings of Geoscience and Remote Sensing Symposium* (*IGARSS'91*) **3,** 3 (1991).
2. D. Yu, L. Zhou, J. Yang, and Y. Peng, Journal of Tsinghua University (Sci. & Tech.) (in Chinese) **45,** 888 (2005).
3. S. Xu and Z. Li, Journal of Zhejiang University (Natural Science) (in Chinese) **29,** 275 (1995).
4. X. Wang, in *Proceedings of ICSP'2006* **1,** 16 (2006).
5. C. Jia, G. Kuang, and Y. Su, Journal of National University of Defense Technology (in Chinese) **26,** 50 (2004).
6. T. Pun, Signal Process. **2,** 223 (1980).
7. G. Dai and R. Zhang, J. Remote Sensing (in Chinese) **11,** 177 (2007).
8. F. Wu, C. Wang, and H. Zhang, in *Proceedings of Geoscience and Remote Sensing Symposium* (*IGARSS'05*) **6,** 25 (2005).
9. F. Su, Z. Wu, and X. Lin, in *Proceedings of 2003 6th International Symposium on Antennas, Propagation and EM Theory* 600 (2003).
10. Y. Li and Y. Zhou, Chin. Opt. Lett. **5,** 509 (2007).