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Identification of Airfield Runways in Synthetic Aperture Radar Images

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Abstract

Synthetic Aperture Radar (SAR) is a microwave-based remote sensing technique whereby images can be captured when optical images cannot, at night or when there is cloud cover. However, its very low signal-to-noise ratio (1:1) means that conventional image analysis techniques are unsuitable for SAR imagery. This paper presents a novel approach to the detection of very small objects in SAR imagery, which combines a pre-processing stage with a Hough transform analysis stage using contextual information to identify suitable 'signatures'. The result of this procedure is the fast and accurate identification of airfield runways. The method is based on the fact that the only reliable characteristic of airfield runways visible in SAR images is the location of lights along their sides.

1. Introduction

Synthetic aperture radar (SAR) is a high resolution imaging technique, which utilises one or more microwave transmitters and receivers. It is usually operated from an airborne or spaceborne platform, see for example [1]–[2].

One significant advantage of the technology is that SAR images can be captured when optical images cannot, at night for example, or when there is cloud cover. However, this must be weighed against a characteristic feature of SAR imaging whereby, due to the method of formation, images have a signal to noise ratio of 1:1. As a result, the techniques needed for the successful analysis of a SAR image differ from those normally used for image processing; they are inevitably much more computationally intensive [3].

This paper addresses the problem of analysing SAR images for the purpose of detecting groups of very small objects comprising a required target. In the application described here, the objective is to identify one or more airfield runways by detecting the rows of lights along their sides.

There has been significant research in the detection of moving objects in SAR images (for example [4]). There has also been some interest in the detection of features using SAR imagery in conjunction with some other imagery (e.g., [5]). However, there is no major work on the specific problem of detecting airfield runways in SAR imagery. Moreover, there has been little research into the detection of any small static features in SAR imagery.

In the next section the characteristics of the problem are described and the processes involved in the new approach detailed in separate sub-sections. Finally, Section 3 concludes the paper.

2. The problem and the approach

The characteristics of SAR imaging mean that objects with many sharp edges and corners give a strong return (that is they show as a bright point in a SAR image). Since runway lights have many sharp edges (in their casing), they must be present in a SAR image. Since they occur in parallel straight lines along the edges of the runway, they can be used as a group to reliably identify the runway.

The runway itself will appear dark in SAR images (see Figure 1). However, it is important to note that this fact cannot be relied solely upon. Runways stand out from the surrounding area in fertile landscapes, because the surrounding fields have distinctive texture. However, in more uniform regions (such as desert areas), the runway itself would not be so apparent. Moreover, there is always the danger of wrong identification of other flat-surfaced elongated areas such as canals, for instance, that show in the SAR image in a very similar way to runways.

The problem of analysing a SAR image to detect airfield runways thus becomes one of identifying in the image similarly sized bright points that lie in two parallel, approximately straight lines.

Detecting small static objects using only SAR imagery has a number of problems. The first is the high noise level, as discussed earlier. Whilst this is generally a problem with analysis of SAR imagery, when considering small objects, the bright regions to be identified may be indistinguishable from speckle in some field of crops. The second main problem is that a small object has no shape of its own and instead has a shape produced by the SAR image generation process. It is therefore impossible to enhance the object and factors such as its orientation

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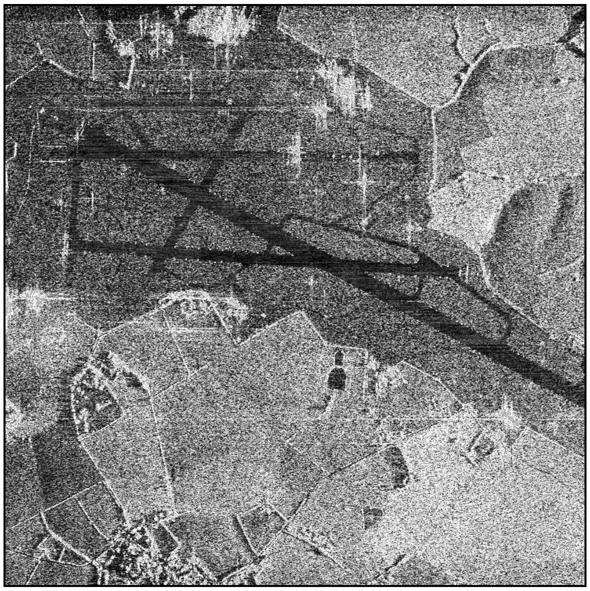

Figure 1. A SAR image containing two airfield runways.

cannot be determined. The approach described here overcomes these problems using contextual information.

For the present problem, the required sets of bright points that were deemed to be relevant, but not too highly specific, are as follows.

Assuming that for each runway there are M identical and 'physically collinear' airfield runway lights along two parallel lines, in the SAR image there will be $N \leq M$ bright spots of similar, but not necessarily the same size or intensity, that lie in two parallel approximately straight lines.

Any variation in size and intensity of the bright points and any missing bright points are the result of the influence of several factors including the grazing angle of the radar when the image was captured, and (significant) noise.

The proposed approach for locating lines of bright points that makes use of the above contextual information involves two stages. The first, the pre-processing stage, filters the raw SAR data, aiming to remove large bright areas of the image and retain small isolated groups of bright pixels. The second, or main processing stage, seeks to recognise the lines of runway lights, by applying the Hough transform and searching for characteristic 'signatures' in the resulting accumulator array.

2.1 Identification of candidate points

The first task of the pre-processing stage is that of identifying those pixels in the image that locally have a relatively high intensity. Such pixels are then grouped together into 'regions of relatively high intensity'. Regions which are either too large, or too small, are discarded, and each of the remainder is represented by a single point. There are thus the following three steps: *local thresholding, region generation* and *region-to-point conversion*. Each of these steps will now be considered in more detail.

The raw image data is transformed into a binary array, *bimage* with the aid of a local thresholding operation using an $n \times n$ window. After this operation, $bimage(i, j) = 1$ if pixel in position (i, j) at the centre of the window is greater than k times the average pixel intensity in the window in the original image, and $bimage(i, j) = 0$ otherwise. The values of $n = 3$ and $k = 5$ were experimentally determined to produce good results. These values are dependent on the resolution of the SAR image, which in the case of the sample airborne SAR images was 1.5 metres per pixel (spaceborne SAR has a resolution of 3 metres per pixel).

At this point, the connected components are identified in the binary image. Many of them will represent random noise rather than a significant target. Correspondingly, an attempt to remove the offending pixels is made by considering the size of such regions.

Since bright points that correspond to the set of sought targets will contain between α and β pixels (the size of each of α and β can be determined from the grazing angle used in capturing the image, and the nature, size, and aspect of the targets), the final operation performed in this pre-processing step involves discarding any region whose size does not lie in the range $[\alpha, \beta]$. For the application described here, $\alpha = 2$ and $\beta = 10$ were experimentally determined to constitute fairly generic bounds for the size of the required regions in a variety of situations.

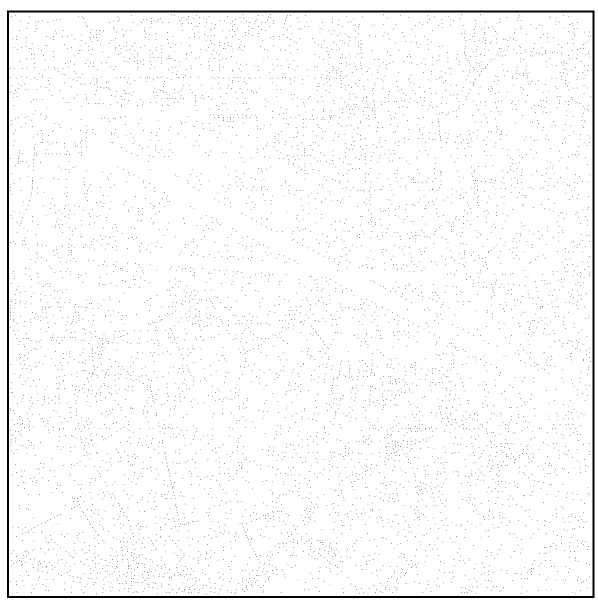

Figure 2. The candidate points resulting from the pre-processing.

Finally, each region is replaced by a single point which represents the location of the 'centre' of the region. This is achieved for each region R of *bimage* by computing the coordinates of the centre of gravity (centroid). The points identified from the image of Figure 1 can be seen in Figure 2.

2.2 Selection of runway lights

Having identified a set of candidate points (in terms of x and y-coordinates) the method proceeds to select those points that correspond to airfield runway lights. As mentioned earlier, it can be safely assumed without loss of generality that the lights are arranged along parallel lines (two for each runway). The problem thus becomes to identify pairs of parallel straight lines in the data.

As can be seen in Figure 2, there is a significantly large number of extraneous points. The natural choice of method to detect straight lines in the presence of noise is the Hough transform [6]. Each point in the x–y plane is transformed into a curve in a ρ–θ plane according to the equation [7]: $\rho = x\cos(\theta) + y\sin(\theta)$. Collinear points in the x–y space correspond to curves intersecting at a particular point in ρ–θ space. An accumulator array is used to count the number of occurrences of curves passing through a particular array cell corresponding to a rectangular region in the ρ–θ space. The idea is that curve intersection points can be identified by detecting cells containing high counts.

Particular care must be taken in choosing the angular resolution $\delta\theta$ and the distance resolution $\delta\rho$. The values should be such that collinear points (x–y) do correspond to curves intersecting at the same Hough accumulator cell. As the total number of θ and ρ values considered (and hence the number of accumulator cells) will have a direct impact on the run-time performance of the method, the coarser resolution that does not compromise the required accuracy is chosen. In the application described in this paper, experimental evidence has shown that $\delta\theta = 4°$ and $\delta\rho = 4$ pixels produce highly accurate results. The angular range is [-90°, 90°].

The accumulator resulting from the application of the Hough transform to the points shown in Figure 2 can be seen in Figure 3. In this figure the accumulator is represented as a greyscale image where darker pixels represent cells with higher counts.

It can be observed in Figure 3 that a number of cells with high counts are present, albeit not clearly distinguishable due to the significant number of curves corresponding to 'noisy' points in the x–y space. The relatively low contrast of the image in Figure 3 should be compared against that of the accumulator resulting from edge images (e.g., [7]) which is relatively high.

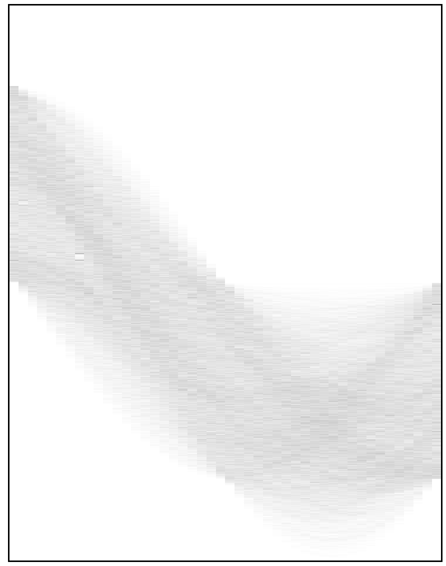

Figure 3. The Hough accumulator array (modified aspect ratio).

It should be noted that the peaks in the accumulator (darkest points) do not necessarily correspond to runway lights. There can be many instances of collinear points corresponding mainly to hedges and other line structures on the ground. It is also possible that the highest peaks do not result from the required lights.

The standard technique would be to search the accumulator and identify all peaks and then select the appropriate ones by applying criteria such as pairwise parallelism etc. However, it is desirable to avoid such time-consuming operations.

The approach described here exploits the fact that the arrangement of the lights on a particular airfield runway creates a characteristic pattern in the Hough accumulator. This pattern can be described as a part of a column (corresponding to a particular angle) of the accumulator that has two distinct peaks with a gap of very low values between them. These two peaks correspond to the two rows of lights on either side (lengthwise) of a runway and their separation is regular (a maximum allowable value can be easily calculated).

A single pass of the accumulator array is sufficient to identify all pairs of lines corresponding to runway lights. The algorithm is as follows:

for each angle θ (column)
  identify a peak which has a shape
    and size > T_s
  identify a peak which has a shape
    and size > T_s
  if the peak distance $T_\rho > \Delta_\rho < T_{\rho 2}$
    a pair of lines of lights has been found.

The distance thresholds $T_{\rho 1}$ and $T_{\rho 2}$ were experimentally determined as 12 and 40 pixels respectively (3 and

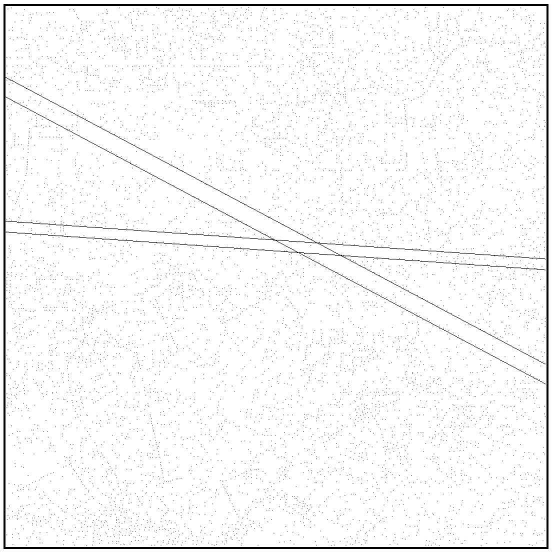

Figure 4. Illustration of the general direction of the identified airfield runways.

10 array elements respectively). Similarly the size threshold T_s was determined as 20 which denotes the minimum number of curves passing through the particular accumulator cell.

If the exact locations of lights are required, further processing takes place to identify all the (x, y) points in the image that lie across the length of the runway (there is not a 1:1 relationship between (ρ, θ) and (x, y) representations due to the relatively coarse quantisation of the ρ–θ space) The spacing between these points can be examined to eliminate points that do not correspond to lights. For illustration purposes, the location and general direction of the straight lines fitted to the points of the detected runways can be seen in Figure 4.

It should be noted at this point that, for the purpose of identifying the airfield runways, it is sufficient to terminate the process when the (ρ, θ) representation of the lines has been identified in the accumulator data.

3. Results and Conclusions

A typical example of a SAR image and the intermediate and final results obtained has been presented in Figures 1 to 4. The image shown in Figure 1 contains two runways that cross one another and its size is 1000×1000 pixels.

The method has been implemented in the C programming language without any optimisation effort. The time taken by the pre-processing stage is typically in the region of 8 CPU seconds on an HP 9000/777 series standard multi-user system. The Hough transform takes roughly a further 0.7 of a CPU second. This combined processing time of 8.7 CPU seconds compares favourably to an earlier method, which used a 'brute force' line-growing technique and which takes an average of 1.2 CPU minutes per image for the same data on the same machine.

This paper has addressed the problem of analysing SAR images for the purpose of identifying very small objects. In particular, an approach for detecting airfield runways has been described. In virtue of the high noise level in SAR images, and the computational cost of processing them, the approach has been designed to utilise contextual information. By a considered choice of such information, it has been possible to engineer the approach so as both to render it appropriate for a wide range of situations, and to reduce the computational burden associated with the applications in that range. The effectiveness of the approach has been illustrated by means of an example involving the detection of airfield runway lights.

Future work will concentrate on the pre-processing stage of the approach described here. In related work to identify lines of electricity pylons, it was discovered that the use of an artificial neural network in the pre-processing stage improved both speed and accuracy of the pre-processing and hence also improved the speed of the main processing stage (since it had fewer points to process) [8]. It is hoped that such improvements can be reproduced for the airfield runways problem described here.

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