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# Aircraft recognition in high-resolution using wavelet transform features

**S Manju, Padmapriya R, SharonShanthini P, Nithya T**
Department of Electronics & Communication engineering, Velammal Institute of Technology, Thiruvallur.
***Corresponding author: E-Mail: manishajahan@gmail.com**

**ABSTRACT**

This project is proposed to recognize an aircraft in satellite image using template matching for accurate detection and tracking. Aircraft recognition is an important issue of target recognition in satellite images and has many important applications in practice. Aircraft on the wavelet based method, we propose a hybrid recognition method that combines wavelet features and correlation changes. Here, filter process and feature extraction of guassian noise removal is done by wavelet transform. Each subband can vary in number and the types of features, where these two degrees of variability empower the hybrid method with even more flexibility and discriminative potential on recognition on aircraft. The performance of these used algorithms will be differentiated though precision and recall rate metrics. These results show the proposed shape primitives are indeed sufficiently powerful to aircraft recognize in satellite remote sensing images. The target then modeled by extracting both spectral and spatial features. In target matching procedure, template will be used as matching model to recognize with each frame by frame for accurate detection.

**KEYWORDS:** Aircraft image, Wavelet features, Template matching.

## 1. INTRODUCTION

Aircraft Object tracking in a complex environment has long been an interesting and challenging problem. As aircraft recognition is still a challenging problem, we want to further investigate how we can resolve issues in this field. Aircraft recognition is different from other natural object recognition. This project presents the recognition of the object (Aircraft) in an image for better recognition based on the combination of wavelet features and correlation on shape analysis. An object can also be recognized with the help of texture or appearance features through Scale Invariant Feature Transform (Wavelet Transform).These correlation measurement and SIFT for appearance feature extraction are effectively utilized for accurate object recognition. Along with this system, Gaussian noise features removal also used to extract the minimal luminance changes from images for better performance. These techniques are useful to minimize the drawback of previous methods like texture features and OTSU (multi-scale segmentation).As number types is limited and each type of aircraft has fixed size and shape. Considering the above characteristics, we can build a template for each type and match the test aircraft to the different types of templates. The recognition approach consists of two steps: direction estimation and type recognition. In the approach, a direction estimation method is proposed first to align aircraft to a same direction

**Description**

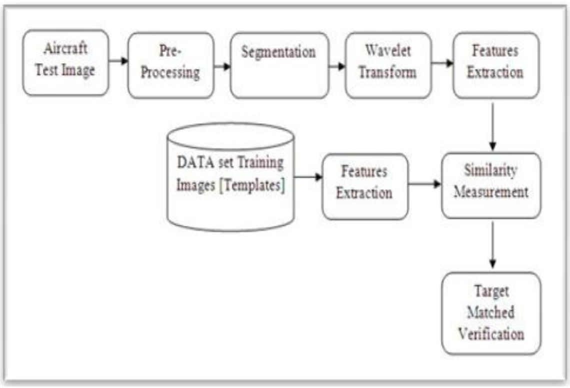


**Figure.1. block diagram**

## 2. MATERIALS AND METHODS

**Preprocessing:** Generally it is done to remove the unwanted noise in the captured image by the histogram analysis. After the processing, the original image is recovered from the captured one followed by that direction estimation is as done.

**Direction Estimation:** Considering the shape characteristics of aircraft such as symmetry and fuselage characteristics, we estimate the directions of aircraft with histograms of oriented gradients (Dalal, 2005) for aircraft alignment. The flow of direction estimation is as follows.

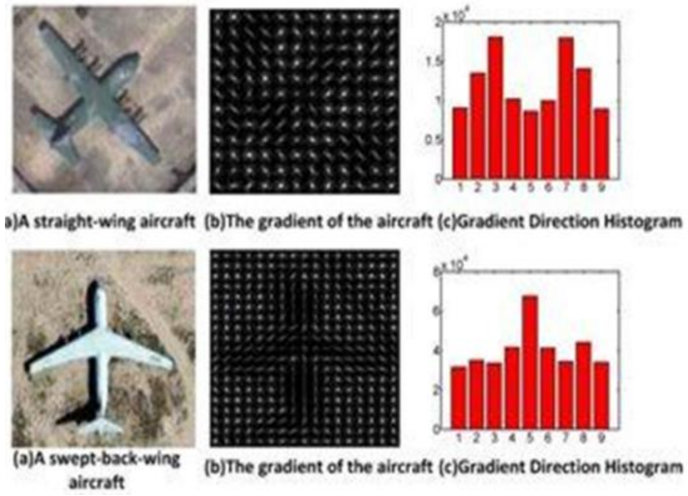


**Fig.2.Direction Estimation**

- The first step is to calculate the gradient of the image to get the contour and texture information and then to weaken the interference caused by image brightness changing.
- The histograms of oriented gradients is a histogram in nature, such as an image histogram. For an image histogram, the *x*-axis means the range of pixel value, from 0 to 255 for 8-bitimages, and the *y*-axis means the votes accumulated into each value in the *x*-axis. For histograms of oriented gradients, the *x*-axis means the range of the orientation of the pixel's gradient, from 0˚to 180˚.The *y*-axis means the votes accumulated into each orientation bin in the *x*-axis. Therefore, in this step, each pixel calculates a weighted vote for an edge orientation histogram channel based on the orientation of the gradient element centered on it, and the votes are accumulated into orientation bins. The orientation bins are evenly spaced over 0 –180.
- The line structures of aircraft lie in the fuselages and the wings, and the direction of fuselage indicates the direction of aircraft. The orientation of the fuselage usually corresponds to one of the first three maxima in the gradient direction histogram. Therefore, those first three maxima are selected as potential candidates for aircraft orientation.

**Segmentation:** Image segmentation is a process of portioning an image into non-intersecting regions such that each region is homogenous. Here histogram probability threshold selection is used which overcomes the problem of existing algorithms. It is used to measure the average foreground and background variance to suppress the redundant region to zero's and set one's to desired foreground region.

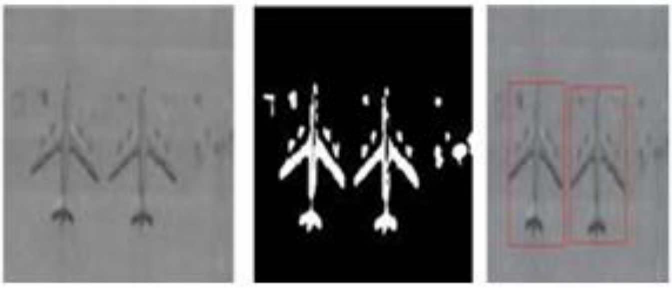

**Figure.3.Segmentation of aircraft image**

**Wavelet Transform:** Wavelet transform is a local transformation from time to frequency domain and easily generate a variety of different resolution images. It decomposes the image into different subband images namely LL, LH, HL, HH. A high-frequency subband contains the edge information of input image and LL subband contains the clear information about the image. A data reduction method will be applied to each image for converting multiband to single band images using transfer.

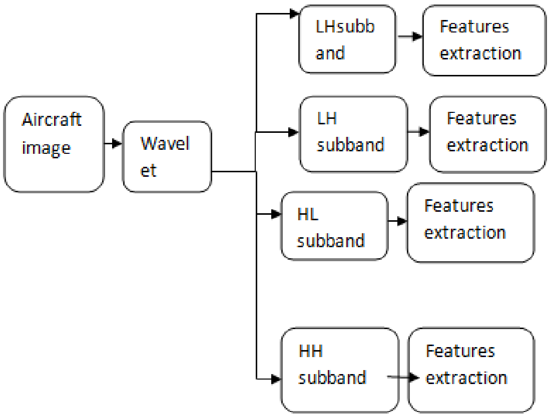


**Figure.4.Wavelet transform**

**Features extraction:**

**Entropy:** Entropy gives a measure of complexity of the image. Complex textures tend to have higher entropy

**Where,**

P (i, j) is the co-occurrence matrix

**Contrast:** Measures the local variations and texture of shadow depth in the gray level co-occurrence matrix.

**Correlation Coefficient:** Measures the joint probability occurrence of the specified pixel pairs.

$sum(sum((x-\mu x)(y-\mu y)p(x, y)/\sigma_x\sigma_y))$

**Template Matching:** It is a technique in digital image processing for finding small parts of an image which match a template image. A sliding window over other image sequences is used to indicate the possible presence of the reference target. A regional feature matching operator is applied to find the similarity between the target model and the pixels within the window.

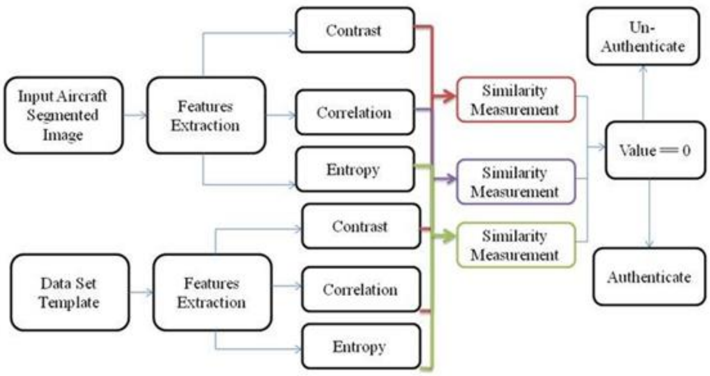


**Figure.5. Template Matching**

**3. EXPERIMENTAL RESULTS AND DISCUSSION**

Figure 6 shows the seven types of aircraft for recognition. In this figure, each row includes four testing samples of a type and the template corresponding to the type. After direction estimation with our proposed method and alignment, the directions of aircraft are almost upright. We generate segments with four-scale segmentation, and the seg-mentation in each scale is based on the number of segments in an image as a parameter, i.e., 30, 60, 90, and 120.

For convenience of comparison, the results for the whole data set based on both our approach and the referenced methods are listed in Table 1. We use the method in (Fu, 2011), which is based on the moment invariants methods, as the reference method 1 and the method in (Yanan, 2009), which is based on the methods including direction estimation phase, as the reference method 2.

It is shown in Table 1 that the accuracy of the baseline method is obviously lower than the proposed method. Fig. 6 shows the confusion matrix when classifying images into one of the seven types. In Fig. 7, we can see an easily confused pair, which is type 1 and type 4, and this could be explained by the fact that the two types are both with straight wings. Another easily confused pair is type 5 and type 6, and this could be explained by the fact that the two types are both with swept-back wings, and with similar sweep back angle.

Now, we analyze the jigsaw matching pursuit algorithm for reconstruction. Figure 7 shows the images reconstructed with each type of test image and corresponding templates. In Figure 7, the column of "Target location" exhibits the performance of our method for locating the targets detected, the column of "Reconstruction" illustrates the reconstructive From Figure 7, we can see that our method can locate and reconstruct the aircraft accurately. Note that there are obvious shadows in type 3 and type 5 testing images, the shapes of which are similar to the actual targets, and accordingly, the location-residual error surfaces of the two images both have more than one obvious troughs that correspond to the resid-ual error of the actual targets and shadows, respectively. The location-residual error surfaces of other types without obvious shadows have one obvious trough.

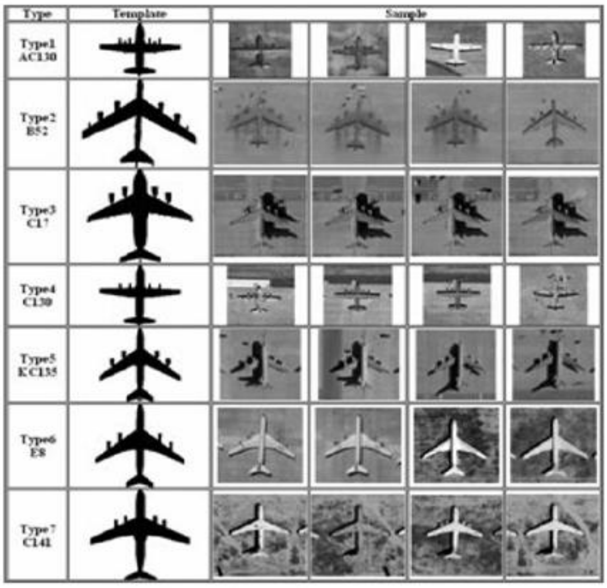


**Figure.6.Seven types of Aircraft and the Template corresponding to the type**

**Table.1. Recognition Accuracy using Different Methods**

| | Proposed method | Referenced method 1 | Referenced method 2 |
|---|---|---|---|
| Accuracy | 92.9% | 83.3% | 89.0% |

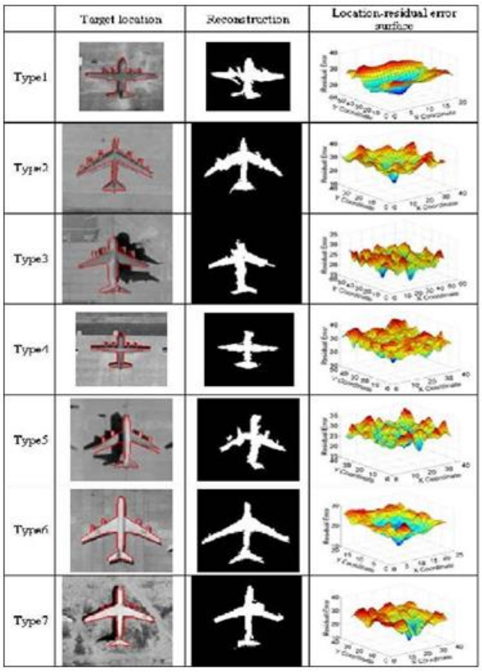


**Fig.7.Types of Aircraft and Templates**

## 4. CONCLUSION

In this letter, a new robust-type recognition method for aircraft targets in high-resolution remote sensing images has been proposed. The main advantage of the method lies in that the method can recognize aircraft robustly and excludes the target overall shape extraction phase, which is usually included in the traditional recognition methods and is not practical due to disturbing background. Experimental results show that our recognition method yields a good performance.

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