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Aircraft Recognition in High Resolution Satellite Images

[1] P.C.Hemalatha, [2,] Mrs.M.Anitha M.E.,
[1] *M.E-Applied Electronics,* [2] *Assistant Professor,*
Department of ECE, Sri Muthukumaran Institute of Technology, Chennai, India,

ABSTRACT
The project presents recognize of an aircraft in satellite image using template matching for accurate detection and tracking. High resolution multispectral satellite images with multi-angular look capability have tremendous potential applications. Here the system involves an object tracking algorithm with three-step processing that includes moving object estimation, target modelling, and target matching. Potentially moving objects are first identified on the time-series images. The target is then modelled by extracting both spectral and spatial features. In the target matching procedure, template will be used as matching model to recognize with each frame by frame for accurate detection. Here, normalized cross correlation and spatial features are used as features model for recognition. This recognition model will be continued for all sequence of satellite images.

Keywords: *aircraft matching. Segmentation, template matching*

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I. INTRODUCTION

The identification of objects in an image. This process would probably start with image processing techniques such as noise removal, followed by (low-level) feature extraction to locate lines, regions and possibly areas with certain textures. However, automatic aircraft recognition is not a simple problem. Besides the complex structure, different aircraft differ in size, shape, and color, and even for one kind of aircraft, the texture and intensity are usually dissimilar in different scenarios. Moreover, recognition often suffers from various disturbances such as clutter, different contrasts, and intensity inhomogeneity. Thus, the robustness and resistance to disturbance are highly required for the method.

The clever bit is to interpret collections of these shapes as single objects, e.g. cars on a road, boxes on a conveyor belt or cancerous cells on a microscope slide. One reason this is an AI problem is that an object can appear very different when viewed from different angles or under different lighting. Another problem is deciding what features belong to what object and which are background or shadows etc. The human visual system performs these tasks mostly unconsciously but a computer requires skilful programming and lots of processing power to approach human performance. Manipulating data in the form of an image through several possible techniques. An image is usually interpreted as a two-dimensional array of brightness values, and is most familiarly represented by such patterns as those of a photographic print, slide, television screen, or movie screen. An image can be processed optically or digitally with a computer.

II. PRINCIPAL COMPONENT ANALYSIS

PCA is a mathematical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it be orthogonal to (i.e., uncorrelated with) the preceding components. Principal components are guaranteed to be independent only if the data set is jointly normally distributed. PCA is sensitive to the relative scaling of the original

variables. Depending on the field of application, it is also named the discrete Karhunen–Loève transform (KLT), the Hotelling transform or proper orthogonal decomposition (POD).

A.Algorithm Flow:

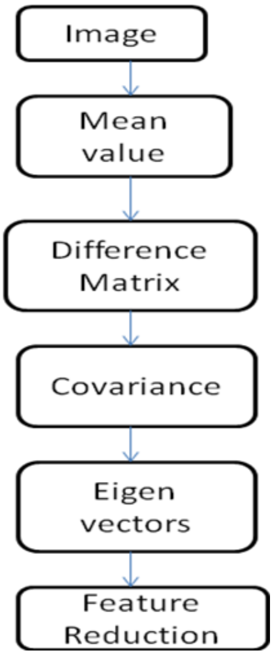


Fig1. Flow of band reduction process

*B.PCA steps***:**

1) Input.
2) Subtract the mean
3) Calculate the covariance matrix
4) Calculate the eigenvectors and eigen values of the covariance matrix
5) Choosing components and forming a feature vector
6) Deriving the new data set.

The singular value decomposition of **X** is $\mathbf{X} = \mathbf{W}\square\mathbf{V}^{\mathbf{T}}$, where the $m \times m$ matrix **W** is the matrix of eigenvectors of the covariance matrix $\mathbf{XX}^{T}$, the matrix $\square$ is an $m \times n$ rectangular diagonal matrix with nonnegative real numbers on the diagonal, and the $n \times n$ matrix **V** is the matrix of eigenvectors of $\mathbf{X}^{T}\mathbf{X}$. The PCA transformation that preserves dimensionality (that is, gives the same number of principal components as original variables) is then given by:

$$Y^{T} = X^{T} W$$
$$= V \sum^{T} W^{T} W$$

$$=V \sum^{T}$$

V is not uniquely defined in the usual case when $m < n - 1$, but **Y** will usually still be uniquely defined. Since **W** (by definition of the SVD of a real matrix) is an orthogonal matrix, each row of $\mathbf{Y}^{T}$ is simply a rotation of the corresponding row of $\mathbf{X}^{T}$. The first column of $\mathbf{Y}^{T}$ is made up of the "scores" of the cases with respect to the "principal" component, the next column has the scores with respect to the "second principal" component.

III. IMAGE SEGMENTATION

Image segmentation is a process of partitioning an image into nonintersecting regions such that each region is homogeneous and the union of two adjacent regions is not homogeneous. Thresholding based methods can be classified according to global or local thresholding and also as either bi-level thresholding or multi thresholding.
For the aforementioned facts, we decided to consider the nonparametric and unsupervised Otsu's thresholding method.

The Otsu's thresholding method may be recommended as the simplest and standard method for automatic threshold selection, which can be applied to various practical problems. Although the Otsu's thresholding method is usually applied to images with a bimodal histogram, it may also provide a meaningful result for unmoral or multimodal histograms where a precise delineation of the objects present on the scene is not a requirement. The key concept behind this method is to obtain an optimal threshold that maximizes a function of the threshold level. The optimal threshold is selected by a discriminant criterion, in order to maximize the separability of the resultant classes in gray levels. The procedure utilizes only the zeroth- and the first-order cumulative moments of the gray level histogram.
The equations involved are as follows:

The threshold is selected that minimizes the intra-class variance (within class variance), defined as a weighted sum of variances of the two classes and between class variance are,

$$\sigma_{B} = \omega_B(\mu_{0} - \mu_{1})^2 + \omega_B(\mu_{1} - \mu_{r})^2$$

$$\sigma_{B} = \omega_0 \sigma_0 + \omega_1 \sigma_1$$

Where,

σ_B – Between class variance and σ_W – Within class variance

σ_0 , σ_1 , σ_T are variances for target, background and images.

μ_0 , μ_1 , μ_T are mean for target, background and image.

P(i) is the probability

W_0, W_1 are the probabilities of target and background

The means are determined by,

$$\mu_0 = \sum_{I=1}^{K} \frac{\mathrm{ip(i)}}{\omega 0}$$

$$\mu_1 = \sum_{I=k+1}^{L} \frac{\mathrm{ip(i)}}{\omega 1}$$

$$\omega_0 = \sum_{i=1}^{k} \mathrm{p(i)}_I = \omega(k)$$

$$\omega_0 = \sum_{i=1}^{k} \mathrm{p(i)}_I = \omega(k)$$

Thresholding is a very simple form of segmentation. A threshold is defined, and then every pixel in an image is compared with this threshold. If the pixel lies above the threshold it will be marked as foreground, and if it is below the threshold as background. The threshold will most often be intensity or color value. Other forms of thresholding exist where the threshold is allowed to vary across the image, but thresholding is a primitive technique, and will only work for very simple segmentation tasks.

Thresholding is a non-linear operation that converts a gray-scale image into a binary image where the two levels are assigned to pixels that are below or above the specified threshold value. In this method the selection of initial threshold value is depends upon the histogram of an image and the gray scale of an image.

IV. AIRCRAFT DETECTION

An Aircraft from the satellite images are detected using templates 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. The lebelled component from segmentation module will be applied to extract the region features to describe its characteristics. Here correlation coefficient will be used to measure the similarity between two different objects for target detection and tracking.

C.Correlation Coefficient: It is used to find the similarity between two different objects with their region features. It will be described by,

Cor_coef = [**sum(sum(u1.*u2))] /[sqrt(sum(sum(u1.*u1))*sum(sum(u2.*u2)))];**

Where, u1 = F1 – mean of F1, u2 = F2 – mean of F2

F1 – Feature set1 and F2 – Features set2

V. EXPERIMENTAL RESULTS

The detection and tracking system for aircraft recognition based on templates. Here for experiments, the selected templates with different shape model and it is shown that are,

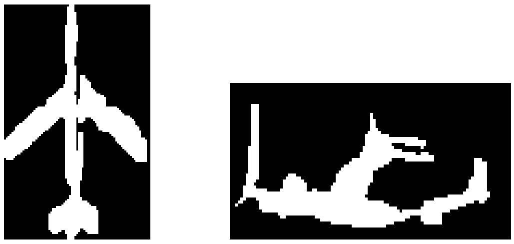
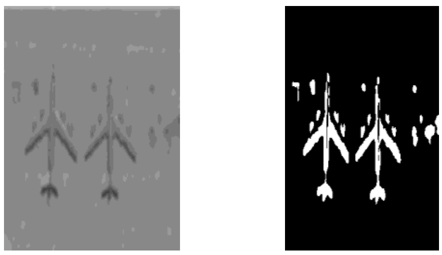
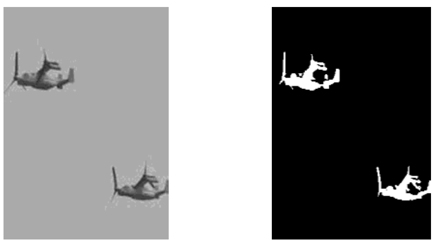


Fig2. **Templates with different shapes**

From the segmented regions of input image, the local object descriptors are evaluated to characterize the shape of an object. Each object features are matched with available templates descriptors to detect the location to track the target, the obtained results are listed as below,



(a) **(b)**



(c) **(d)**

Fig3. Segmentation (a) and (b) are taken image, (c) and (d) are otsu segmented image

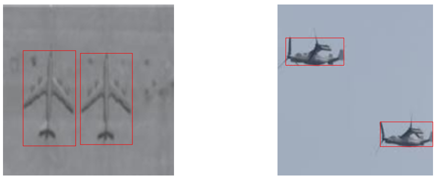


Fig4. Aircrafts tracking

These experiments for aircraft recognition were implemented with the help of MATLAB software and image processing toolbox.

VI. CONCLUSION

The project presented the aircraft recognition from satellites images for surveillance application with an Otsu segmentation and template matching model. The tracking system provides the result with low computational complexity and better accuracy. Morphological and connected component analysis was utilized effectively for enhancing a segmented regions and tracking target objects. Finally the simulated result was shown that better efficiency achieved with chosen techniques and methodologies.

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