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Research on Key Techniques of Regional Detection Method Based on Significance

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***Abstract*—In this paper, the separation and detection methods of key components in the detection of airborne transmission lines are studied, and the separation of key components is detected by significant regional detection. In view of the problems in the detection of feature areas, the global feature extraction and local feature extraction are studied respectively in this paper. The problem of regional detection and feature description of local feature extraction is also studied.**

***Keywords*—Visual Saliency , Global Feature Extraction, Local feature Extraction, Corner Point Detection**

I. Introduction

The regular inspection of airborne transmission lines is an important work to effectively ensure the safety and normal transportation of transmission lines. With the wide application of UAV, the inspection of UAV instead of manual application to transmission line is the trend of transmission route inspection for the future. For the processing of inspection images, the extraction and recognition of target images is a key technology [1].Because of the complexity of the background and the diversity of its changes, the difference between the target image and the background image is very small, so the extraction of the target image and the removal of the background is a bottleneck problem in the inspection image processing.

In this paper, the significance is introduced into the study of feature area detection, aiming at the feature matching and target recognition in the detection of airborne transmission lines, this paper studies the global feature extraction and local feature extraction respectively, and studies the regional detection and feature description of local feature extraction. Several key problems of regional significance are also discussed.

II. Feature Extraction

Feature extraction is one of the basic processing steps of many visual tasks, which is generally divided into two steps of regional detection and regional feature description.The region detection algorithm looks for representative areas in the image, such as corner area, local extremum region, etc.The region description algorithm extracts the eigenvectors for the detected feature regions and takes this as input for subsequent processing.It can be seen that in feature extraction, the selection of feature regions is directly related to the application effect of subsequent algorithms.For example, when feature matching is performed, we enter the description vector of the feature region into the search algorithm to find the description vector closest to the vector distance, and the region corresponding to the nearest description vector is used as the matching area of the area of interest.If the image contains a large number of low-contrast regions and a small number of high-contrast regions, we tend to select High contrast regions (such as corner areas, etc.) as feature areas to complete feature matching, because high contrast regions in this case have a greater possibility to find the correct match, if we choose the low contrast region as the feature area, Will reduce the final match rate.

There have been two different approaches to the construction of visual attention mechanisms: a bottom-up approach and a top-down approach.The top-down approach requires prior knowledge of the task to be completed[2], while the bottom-up approach is data-driven and independent of the task.Feature extraction is an important part of computer vision related research, and the traditional feature extraction method can be divided into global feature extraction method and local feature extraction method.

A. Global Feature Extraction

The global feature extraction method directly uses the entire image region of the target as the representation of the target, which usually clips the entire image to the target size of interest, and then uses the feature description method to quantify the representation.The global feature extraction method uses the grayscale value, pixel gradient, edge or shape of the target as the feature description[3-4].This kind of method has the advantages of simple algorithm principle, fast processing speed and so

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on.Therefore, in the early stage of feature extraction research, the global feature extraction method is sought after by researchers.

The global feature extraction method can find that the method based on subspace representation is too strict for training data and test data, so the result of the algorithm based on this method is greatly affected by the attitude change, occlusion and so on of the target in the image.Although the global feature representation method based on statistical theory disrupts the feature spatial order, so that the global feature method is still effective in the face of the target image with slight attitude change or alignment, but the global feature still has the problem that can not deal with the target part occlusion, the angle of view changes in time non-rigid target and so on, Therefore, most feature extraction studies then turn to local feature extraction.

B. Local Feature Extraction.

The research on local feature extraction has a great influence on target recognition, so that target recognition also has robust recognition results in the case of local occlusion and attitude change.Local feature extraction is generally divided into two steps of Bureau domain detection and feature description.

III. THE METHOD OF LOCAL FEATURE EXTRACTION.

Summarizing the Global feature extraction method, it can be found that the method based on subspace representation is too strict for training data and test data, so the result of the algorithm based on this method is greatly affected by the attitude change, occlusion and so on of the target in the image.Although the global feature representation method based on statistical theory disrupts the spatial order of features, so that the global feature method is still effective in the face of a slight attitude change or not aligned target image, but the global characteristics still can not deal with the target part occlusion, the perspective change and the identification of non-rigid targets and so on. Therefore, most feature extraction studies then turn to local feature extraction.In this paper, the method of local feature extraction is studied from two aspects of area detection and feature description.

A. Area Detection

Area detection is used to find feature areas (or feature points) in an image[5], and this part of the feature area can be reliably positioned when the imaging conditions change, the angle of view changes, or even the noise appears. For example, the traditional regional detection algorithm considers that the smooth area or the area on the edge of the image does not cooperate as a feature area to complete the subsequent processing process, for the smoothing region;It is not possible to accurately distinguish between the region and the adjacent smoothing area, and for the edge region, it is not possible to distinguish between the region and other areas on the edge.

Harris Corner Detection uses a second-order matrix C to look for feature areas, positioning C when the two eigenvalues are large when the local area as a feature area.Matrix C is expressed as :

$$C(x,\sigma,\tilde{\sigma}) = N(x,\tilde{\sigma}) * \begin{bmatrix} I_x^2(x,\sigma) & I_x\, I_y\,(x,\sigma) \\ I_x\, I_y\,(x,\sigma) & I_y^2(x,\sigma) \end{bmatrix}$$

Among them, ν (x,σ̃) is a Gaussian coefficient matrix with X as the center and the variance of σ̃, ν (x,σ̃) is used to set the contribution degree of pixels around pixel x according to the similarity of grayscale value;Ix is the first derivative of the pixel x direction,Iy is the first derivative of the pixel y direction, and Sigma is the size of the local area, that is, the scale, when calculating the corner point.The above formula can be deduced as:

$$C = R^{-1}\begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} R$$

In Equation (2), R is a rotational matrix, and λ1 and λ2 are eigenvalues, which reflect the change rate of two directions respectively.When the λ1 and λ2 are small, the image area is represented as a flatter region, and when one of the values is large, the local area is represented as the class edge region, while the corner area is larger than the two value.In the actual use process, in order to avoid the accurate calculation of λ1 and λ2, the following formula is usually used to determine whether the detection area is a corner area:

$$\det(C) - \alpha * \mathrm{trace}(C) > \mathrm{threshold}$$

where Det (c) is the determinant of Matrix C, Trace (c) is a trace of C, and Alpha is usually set to 0.05.The detected corner area can be described by using descriptors such as PCA[6，10], LDA[7], or sift, and the eigenvectors obtained after the feature description are the local characteristics of the region.

The algorithm relies on a fixed scale sigma, so the Harris angular point detection algorithm does not have good scale invariance, in order to make the feature area have affine invariance, Krystian and other people based on Harris-laplacian and Hessian-laplacian region detection algorithm, The respective regional detection algorithms for affine invariance are proposed respectively.Because scale invariance can be detected by circular operators (such as log), the affine invariance is based on elliptic operators (similar Equation (2)).

B. Feature Description

Use a vector or matrix to describe the detected feature points, regions. Similar to global feature description, local feature description can also use PCA, LDA and other methods to describe feature points or regions.In order to complete the illumination invariance, rotational invariance and displacement invariance of feature description, Lowe proposes SIFT (Scale invariant Feature Transform) descriptor, SIFT algorithm contains two steps, the first step is to use Gaussian difference algorithm (difference The local extremum in different scale space is positioned as the characteristic region[8-9], and this step mainly completes the scale invariance of the feature. Gaussian Secondly, the SIFT is used to extract the eigenvector from the feature region, which mainly makes the feature have rotational invariance.

In order to make the dog look for local extremum points in different scale space, it is necessary to construct the image pyramid, for a pair of image I, to establish its image at different scales, called the sub Eight degree (octave).The first child eight degree selection is based on the original image, followed by each child eight degrees for the last child eight degrees drop sampling results (in the original diagram horizontal, longitudinal two respectively for 1/2 drop sampling), so the composition of the sub-eight degree is the upper layer of the image pyramid. Each child eight degrees general 3-5-layer image, each layer image relative to the previous layer of the image using a larger scale of Gaussian convolution kernel blur. Gaussian differential images are obtained by layer 22 subtraction of the internal image for each child eight degrees.

where $k = 2^{1/K}$, K is the number of image hierarchies within eight degrees per child.

These Gaussian differential images D (x,σ) are images at various scales. This point is a feature point at this scale if the point bit is at the same scale 8 adjacent points, up and down adjacent two-scale images with the point as the center 3*3 the maximum or minimum value of all points in the neighborhood .To remove the characteristic points with strong low contrast and edge response, the remaining feature points are the feature points detected by the SIFT algorithm. The second step is to use the SIFT descriptor to extract the eigenvectors from the detected feature points .In order to make the feature rotational invariance, the algorithm needs to correct the direction of each detected feature point in the local domain .By using histogram to statistic the gradient distribution in the neighborhood of the feature point (statistical gradient, it is not directly superimposed on the same importance of all point gradients in the field, but rather gives different weights to the gradients of different points, the weights of each point are inversely proportional to the distance between the point and the feature point), Take the direction with the highest direction frequency in the histogram as the main direction of the region in order to eliminate the influence of the selection transformation on the feature description.

IV. SUMMERY

The method of feature extraction discussed in this paper mainly considers two problems, validity: For all types of images, is the feature area detected by the existing method beneficial to the subsequent application scenario? Completeness: Whether a point that is ignored by an existing method for a particular kind of image must be useless for subsequent applications.

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