Isotropic Surround Suppression based Linear Target Detection using Hough Transform

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***Abstract* -- This paper presents a novel three-stage technique in light of fractal hypothesis and knowledge mining to recognize bridge under complex background in infrared imagery. Firstly, image is segmented using gradient covariance. Edges and corners in an image correspond to 1D (one-dimensional) and 2D discontinuities in the intensity surface of the underlying scene. Edges and corners can be characterized by the distribution of gradients detection. Furthermore, edges with in more texture environs are suppressed by introducing a measure of isotropic surround inhibitor, this results in edge energy by applying lesser weights to edges in texture environs and large weights to strong edges and clear boundaries. To extract lines from segmented edge image improved Hough transform voting scheme is used along with edge energy. This results in extraction of lines. Finally extracted lines are crosswise examined to evaluate the geometric information and the ubieties between bridge and its surrounding area. The experimental results on real-world and synthetic images show that the new method is efficient and effective for extracting bridge in optical images acquired by unmanned aerial vehicle and it improves target detection significantly.**

***Indexed Terms* -- Isotropic surround suppression, Edge detection, Image Field Categorization, Target detection, Bridge detection.**

I. INTRODUCTION

Among the most crucial point in the trade and economy of a country are its airports [1,2] and bridges. Since the major travel routes and economical exchange is dependent on these two entities and they also hold a strong impact on the military and defense of a country it is extremely important to have strict means of surveillance and continuous scrutiny of these areas. It is the dire need of time to upgrade technology and enhance the ways of automatic detection so that such locations can be watched over. These aspects hold the basis of motivation for this paper.

Methodologies for detection can be bifurcated into two ways: (a) Base to top driven information and (b)A top to down gathered knowledge [3,4]. But there can exist variations in the structures of bridges by large margins. Moreover, in case of low detailed images, the ratio of bridge to image becomes too small and hence hard to correctly interpret, making it difficult to carry out a target driven approach. Existing data points towards the usage of knowledge based methodologies for the detection and recognition of bridges [3-6]. D. Chaudhuri [7] classified the multispectral images into eight different types of land-covers by means of the technique "supervised classification". He used the knowledge driven methodologies for this purpose. The classification is carried out at three levels. But there exists a drawback in this technique that holds a liability of overlooking any narrow bridge if it present along with the bridges having varying width in any image. In order to cut down such discrepancies, the water river regions are marked by means of connecting the bridge blank present between the water bodies.

Water segmentation was used for bridge detection by Yuan *et al.* [3] whereas Zhao *et al.* [4] made identifications of land regions and then distinguished the water regions for bridge detection. Xiaohui [5] and Xiaoke [6] suggested the water is a homogenous area for achieving correct segmentations. However, none of these techniques can completely wipe out the interference created by shoals and water clutter [8] and may result in incorrect segmentation of the regions comprising bridges. There exist a number of other algorithms that make use of the parallel line detection scheme where there is a difficulty in getting complete parallel lines of bridge in the images even though there exists a variation in the intensity of grayscale between water and bridge [3, 8].

In case of airport detection, a number of edge pixels may be extracted which can be useless and are present only due to the complex background. This could affect the analysis in an adverse manner. According to previous analysis, man-made objects are absent in the surroundings.

Proposed algorithm locates ROI sub images by single straight line extraction firstly and then they are evaluated for qualification of bridge. Finally, the bridge recognition is achieved precisely by detection of alongside water areas by performing grayscale threshold and evaluation of cornerness Q_{EG}. Even with low image contrast proposed algorithm offers a good viability and precision in recognition of bridge in synthetic IR images.

II. PROPOSED METHODOLOGY

The algorithm extracts corners, edges and vertices in an image where 1D and 2D discontinuities are seen in the intensity surface of the underlying scene. Image feature extraction is done by a two stage paradigm. Both the stages carry out a treelike categorization. For feature extraction, image processing is done in a unidirectional edge and an omnidirectional changing area (a corner) [6]. The Gaussian curvature of correlation function meant for analysis of texture could be applied here [9 , 10]. This motivated the UNIVAR/OMNIVAR categorization approach of local image features. Plessy corner detector is an established operator of the same class in computer vision [11]. Plessy detector makes use of a spatial average of an outer product of gradient vector, which equals the gradient covariance.

Consider the cross-correlations between f_x and f_y as

$$< \begin{bmatrix} f_x \\ f_y \end{bmatrix} [f_x f_y] > = \begin{bmatrix} < f_x^{\,2} > & < f_x f_y > \\ < f_y f_x > & < f_y^{\,2} > \end{bmatrix} = \begin{bmatrix} S_{xx} & S_{xy} \\ S_{xy} & S_{yy} \end{bmatrix} \qquad (1)$$

Where,

$$< . > \doteq \iint_{\text{ſ}} dx.dy$$

Which shows an integral corresponding to small region ſ. Let λ be an eigenvalue of this matrix. Since it is a solution of

$$\begin{bmatrix} S_{xx} - \lambda & S_{xy} \\ S_{xy} & S_{yy} - \lambda \end{bmatrix}$$

$$(S_{xx} - \lambda)\,(S_{yy} - \lambda) - S_{xy}^2 = 0 \qquad (2)$$

Two eigen-values $\lambda_1 \lambda_2$ of the matrix satisfy

$$\lambda_1 + \lambda_2 = S_{xx} + S_{yy} > 0 \qquad (3)$$

$$\lambda_1 \lambda_2 = S_{xx} S_{yy} - S^2_{xy} > 0 \qquad (4)$$

Its discriminant is

$$(S_{xx}+S_{yy})^2 - 4(S_{xx}S_{yy} - S^2_{xy}) = (S_{xx}+S_{yy})^2 + 4S^2_{xy} \geq 0 \qquad (5)$$

In actually $\lambda_1 \lambda_2$ are variances of two principalcomponents of the f_x and f_y

Homogeneity measure $\mathbf{Q_{EG}}$ is dimensionless and normalized

$$0 \leq Q_{EG} \leq 1 \qquad (6)$$

$$Q_{EG} = \left\{\frac{\sqrt{\lambda 1 \lambda 2}}{(\lambda 1 + \lambda 2)/2}\right\}^2 = 4(S_{xx}S_{yy} - S^2_{xy}) / (S_{xx}+S_{yy})^2 \qquad (7)$$

Complementary measure of $\mathbf{Q_{EG}}$ is $\mathbf{P_{EG}}$. Which is also dimensionless and normalized.

$$0 \leq P_{EG} \leq 1 \qquad (8)$$

$$P_{EG} = 1 - Q_{EG} = (S_{xx} - S_{yy})^2 + 4(S^2_{xy}) / (S_{xx}+S_{yy})^2 \qquad (9)$$

Where $\mathbf{P_{EG}}$ and $\mathbf{Q_{EG}}$ are edge and corner respectively. Grayness variation which should be classified by P_{EG} or Q_{EG}. Blob and Saddle patterns are shown in Figure 1 Following are the properties of PEG and QEG:

- PEG reaches 1 in slants of grayness.
- PEG reaches 1 near edges or ridges.
- QEG reaches 1 at a center of circular symmetry.
- QEG reaches 1 at a center of rotational periodicity with a period =2.
- QEG reaches 1 at a center of rotational skew periodicity with a period =2.

Slants mean a pattern of grayness which are locally approximated. Edge and ridge refer to patterns of grayness which constitute the following characteristics:

1. They exhibit a quick change of grayness across a line, which shows a step or ridge in cross
2. Along the line, there is a small change in shape of the cross sections.

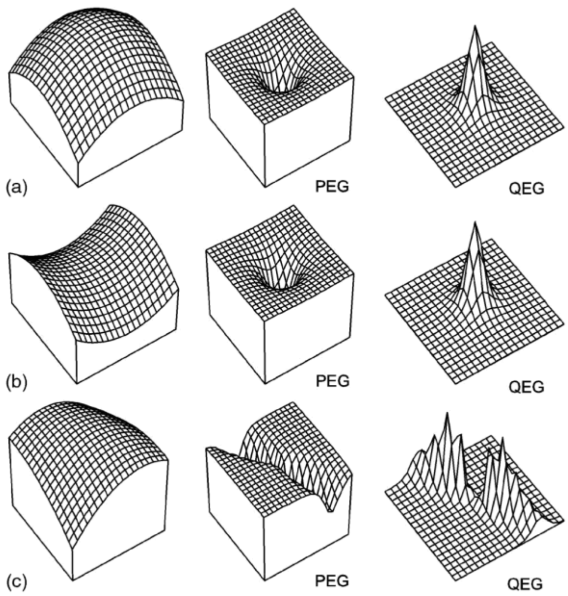


Figure 1. Simulation results of P_{EG} and Q_{EG} for blob and saddle patterns. For each row, the leftmost diagram is an original grayness pattern and those to its right show the response to it.

Once the edge image is formed, its magnitude E is used to formulate edge energy by isotropic surround suppression at any given pixel (x, y). Edges with strong surround suppression carry the lower weights, the votes of edges in texture regions and complex backgrounds are of less implications, resulting in the formation of peaks, are thus lowered or even demolished by surround suppression while on the other hand, edges with peaks accumulated from clear boundaries between dissimilar objects likewise, buildings and sky (background), or roads and vegetation, are upheld or, if lessened, slightly get affected by surround suppression. In this paper the surround suppression used is preferred mainly for its efficacy and intuitive way of describing the confusion of edge pixels that are supposed to be eradicated.

Let $I(r)$ be an input gray level image, with $\mathbf{r} = (x, y) \in \mathbb{R}^2$, and let $\nabla\sigma I(r)$ be its Gaussian gradient defined as the convolution between $I(r)$and the gradient of a Gaussian function $g_\sigma(r)$

$$\nabla\sigma I(r) \triangleq (I * \nabla g_\sigma)(r), g_\sigma(x, y) \triangleq \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2} \quad \mathbf{(10)}$$

The inhibition term is computed as a weighted local average of the Gaussian gradient magnitude$|\nabla\sigma I(r)|$over a ring around each pixel. While weighting function $w_\sigma(x, y)$, defined as a normalized difference of Gaussians:

$$w_\sigma(x, y) = \frac{1}{A}\left|\frac{1}{2\pi k^2\sigma^2} e^{-\frac{x^2+y^2}{2k^2\sigma^2}} - \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}\right| \quad \mathbf{(11)}$$

Where A is a normalization factor defined such that

$$\iint w_\sigma(x, y)\, dx\, dy = 1 \quad \mathbf{(12)}$$

k is the ratio between the scale parameters of the two Gaussians, whose ideal value has been found to be4 and the symbol | . |+ is defined as

$$|u|^+ \triangleq \begin{cases} u, & u > 0 \\ 0, & u <= 0 \end{cases}$$

The weighting function $w_\sigma$with $\sigma = 1$ is shown in Figure 2. The inhibition term $T(r)$ is computed as the convolution of the Gaussian gradient magnitude $|\nabla\sigma(r)|$ with the inhibition filter w_σ (r):

$$T(r) \triangleq \{|\nabla\sigma I| * w_\sigma\}(r)$$

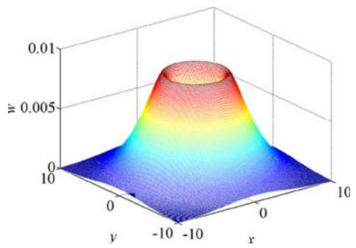
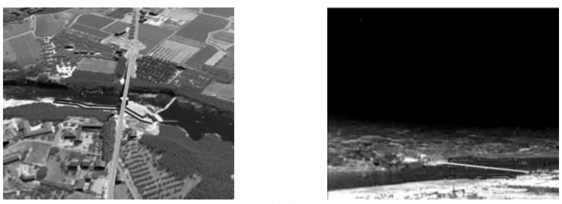
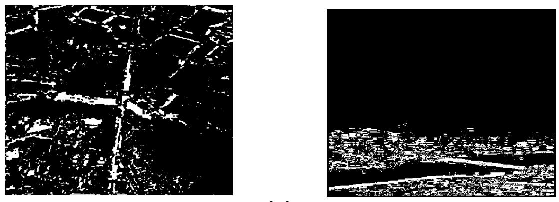


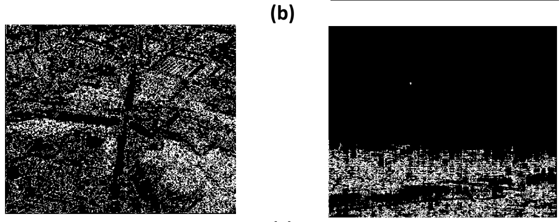
Figure 1 weighting function w_σ



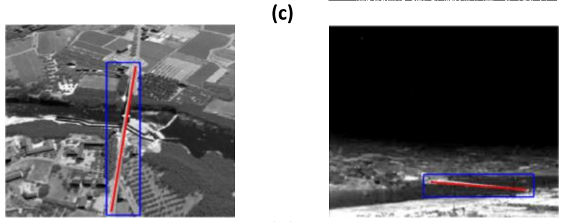
(a)



(b)



(c)



(d)

Figure 3 a) Input Images b) Edge output (P_{EG}) c) Corner output (Q_{EG}) d) Detection results using proposed method

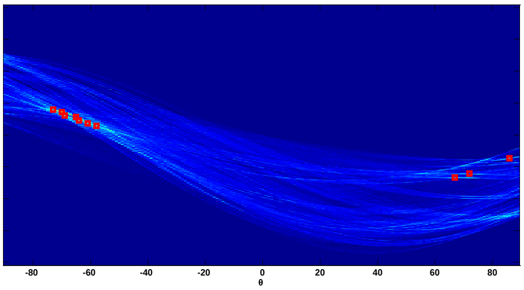
Results of Isotropic surround suppression have been shown in Figure 4.

Figure 4 Isotropic Surround Suppression energy

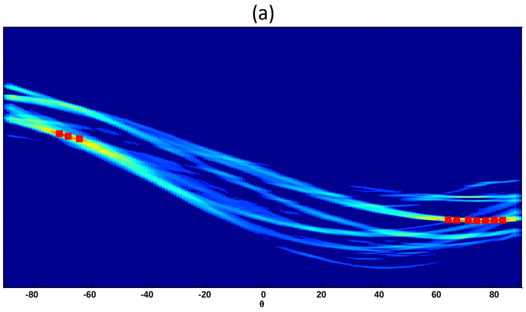
Further region of interest (ROI) is obtained by means of straight line extraction using Hough transform. The Hough transform (HT) (Hough, 1960) is extensively used as one of the typical techniques in computer vision and image analysis. HT has widely been used to locate and detect geometric features such as lines and curves in an image (Duda and Hart, 1972).

Extracted features from input image are mapped on parameter space that generates votes [12] for parameter sets. Features with a large number of votes are identified by searching for significant local maxima in accumulator array. Standard Hough transform and its derived methods with standard voting scheme gives detection rates below expected [13] when used on real world images. One major reason for this decline is the non-linearity of edges. Further, any false peak with high votes in the Hough space suppress a nearby true peak, which leads to a missing line.

Complex background typically do not possess high perceptual importance when segmentation of target body from background or from each other need to be extracted such as finding the region of interest from the surrounding artificial objects. Also some texture regions do have real lines, likewise, lines produced by grills of the bridge. These lines do not describe distinct features defining the object. Instead they are regarded as components of the texture. It is reasonable to suppress the influence of edge pixels formulated by the complex background and texture regions so that quality of peaks detected in Hough space may be lifted. From neurophysiology, this point is also provided that, the presence of a complex surrounding decreases the perceptual importance of the point under concern in human visual system (Knierim and van Essen, 1992; Jones et al., 2001). We have used an approach that works by giving each edge a weight in accordance with the strength of surrounding suppression at the position during its voting into Hough space (Grigorescu et al., 2003, 2004). Figure 5 shows the comparative results of image Figure 1(a) of both techniques using standard Hough transform Figure 4 (b) shows result of an improved Hough transform voting scheme utilizing surround suppression. By introducing a measure of isotropic surround suppression, edge pixels are treated differently. By giving minor weights to texture edges and larger weights to strong and perceptual, and using these weights to accumulate votes in Hough space,this results in reduction of false peaks formed by texture edges which are suppressed, and the quality of detection results is improved.



(a)



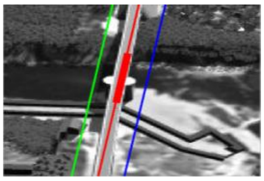
. (b)

Figure 5 a) Peaks shown on Standard Hough space b) Peaks shown on Hough space using voting scheme

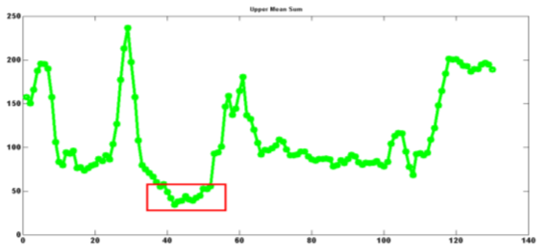
III. TARGET BODY EXTRACTION

This section describes the detection of linear targets using the resulting line(s) which are ROI positions. Proposed method doesn't require the whole water area segmentation. Instead Qeg (cornerness) is used to measure non homogeneity around the target [14]. Figure 6 shows the segmented bridge. The rule based verification sequence which helps to reduce the false alarm in detection of the target is as follows.

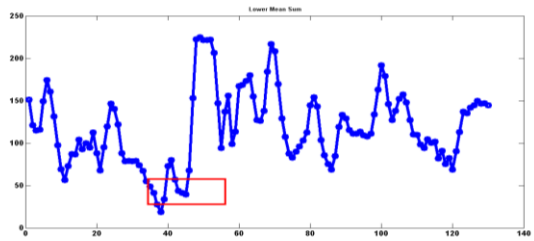
1. The line(s) which are less than known length are eliminated.
2. The cornerness shows that texture density on both side of target easily classify bridge form runway or any man made linear line segment. In case of bridge it should be low as alongside area of water area is homogeneous and flatter.
3. Simple threshold methods often miss the true segmentation of the objects [15]. For this, pixel traversing is used to measure orthogonal intensities alongside target where minimum grayscale values corresponds to high value area. Non homogeneity of surrounding exist in those areas where greater extent of terrain changes or man-made changes occur. Even in that case saliency remains high.
4. The line extracted after the rule based verification will be the particular bridge target.



(a)



(b)



(c)

Figure 6(a) Synthetic image (b-c) Non-uniformity of grayscale values

IV. COMPUTATIONAL TIME

The efficacy of proposed algorithm is shown in this section. Experiments are performed using MATLAB on a machine with 2 GHz processor and memory of 4 GB. It takes about 1 second to process one image. On image size of 576 x 768 following are the computation time.

Methods	Image 1	Image 2	Image 3
P_{EG} / Q_{EG} Detection	0. 6848	0.6515	0.7655
Target Extraction	0.3770	0.3671	0.3003
Total	1.0618 sec	1.1186 sec	1.0658 sec

V. EXPERIMENTAL RESULTS

To validate the efficacy and the extent of the proposed algorithm, 2 images are tested in this paper. The proposed algorithms segment the straight lines and make use of intensity and cornerness to perform validations, so it is able to extract line segments even in low contrast regions.

VI. CONCLUSION

The recognition of linear targets like bridges under the complex background is implemented and it is made clear that proposed algorithm is not specific to any orientation of the target; also it does not rely on any structural formation of the target. Even with low image contrast, proposed algorithm offers a good viability and precision in recognition of linear targets like bridge or runway.

The focus for future work will be mainly in two directions. Firstly, the current work is designed in order to train the object designer in such a way that it identifies objects pertaining to linear shape category. It will further be extended for the detection of different objects pertaining to multiple categories. Secondly, this current work focused on using the spatial information but the future aims include combining it with rich spatial information in order to achieve better and more precise object detection.

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