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Abstract: Real time image detection is still a challenge in research. Several methods have been used, but all can be divide in two approaches: the first is based on image field estimation in this case the quality of image is depending on the estimation method. The second is based on electrons collection, the particularity of this approach is that more the collection time is longer, better will be the quality of image. In both of these approaches, the global image should be obtained by assembling the mosaic local image or the visual index of the different point of the image. In this paper we introduce and Hybrid Fractal Fuzzy theory to track image in real time. The error is minimized using RANSAC (Random Sample Consensus) algorithm, by computing the homograph "pixel" union of image. In practice for mobile image a loop can be realize to focus the image in real time, so, we can have and efficient view of the global image in real time, which confer to the propose approach his efficient flexibility.

Keywords: Fractal Fuzzy Theory, RANSAC Algorithm, Image detection, Optimal Segmentation.

I. Introduction

Microendoscopic image processing is still a challenge for searchers. In practice the quality of images depend of the using materiel likes: microlens, optical interfaces, the multicore fiber (MCF); and the processing theory likes: Neuron network, fuzzy, Wavelet theory etc.. Since, several concepts have been used [1, 2]; the later concepts which is stochastic processing theory, such as attributed points, lines, curves, textures, and lighting variations. All the above concept are based on segmentation theory. Thus, a segmentation algorithm must incorporate many families of image models and its performance is upper bounded by the accuracy of its image models. Real word image are fundamentally ambiguous and our perception of an images are fundamentally ambiguous and changes over time.

For all the processing theories the quality of the image depends on the segmentation method [3, 4]. The objective of image segmentation is to parse an image into its constituent components. Moreover, regarding the popular Hough transform, there are problems with a detection of objects due to blurred and spurious peaks in the accumulators. The problematic of segmentation is that in many images edge are not continuous [4, 5, 6]. So an efficient method is needed to detect all the edges; to improve the quality of segmentation we used fractal theory. Fractal image processing theory should be a new approach and a good theory for edge detection. Since these few years this theory is largely used in image processing.

Fractal theory is a new geometry theory developed by Mandelbrot and Fischer [7, 8, 9, 10]. It is an application of chaos theory; since it have been used in different field (Chakraborti *et al*., 2003). The main drawback of fractal theory is the consuming time of encoding. To reduce the encode time; a trend, we use in this paper is to combine robust estimators (RANSAC) with Fractal theory to compute the homograph.

The RANSAC algorithm [10, 11] is a general robust estimator; it has been used successfully for the estimation of homographs, fundamental matrices, and trifocal tensors. The combination of Fractal theory and RANSAC can minimize a geometrically meaningful criterion, use multi-fractal concept we can also improve the quality of edge detection [10, 12, 13]. It is capable of interpreting and smoothing data containing a significant percentage of gross errors. For each sample a model hypothesis is constructed by computing the model parameters using the sample data.

The disadvantage of RANSAC algorithm is that the estimate is only correct with a certain probability, because it's a randomized estimator. To reduce this process, we use fuzzy theory, so the encoding time is minimized. The structure of the RANSAC algorithm is simple but powerful. Each point has the same probability of selection (uniform point sampling) [14, 15].

The paper is organized as the follow: the second section is focused on Fractal image processing theory, the third presented fuzzy theory, in the fourth we presented the error optimization, in section five we present the algorithm; the result of our simulation are been proposed in section five and the conclusion in section six.

II. Fractal Theory

II.1 Preliminaries

Fractal geometric is based on affine transformation, which is definite by:

$$\tau^n : A^\alpha(X) = X^{k+1} = AX^k + b \qquad (1)$$

In equation (1) A^α, τ^n are respectively the associate matrix and the affine isometric transform. where

$$A^\alpha = \begin{pmatrix} a_{11} & a_{11} \\ a_{11} & a_{11} \end{pmatrix} \in R^{2\times 2} \text{ and } b = \begin{pmatrix} b_1 \\ b_2 \end{pmatrix} \in R^2 \qquad (2)$$

$X = (x \ \ y)^T$ the coordinates of a pixel; and by $\alpha = [a_{11}\ a_{12}\ a_{21}\ a_{22}\ b_1\ b_2] \in R^6$ the parameters of a given transformation. The linear iterative matrix A_α is convergent if for all X^0 the sequence X^k converges to a limit that is independent of X^0. To satisfy this condition Banack [10] fix point theory is a necessary and sufficient condition for the convergence of this affine transformation (Eq 1) must be realized for $\rho(A^\alpha) < 1$; where $\rho(\ )$ is a spectral radius of A^α.

II.2 Fractal Theory of Image processing

In fractal image encoding theory, the encode image is partitioning in a set of domain block N_d : $d^1, d^2, ..., d^N \in R^n$, which can be overlapped and a set of range block N_r $r^1, r^2, ...r^N \in R^n$ the size of the domain block is the double of the range block. The concept of fractal encoding is that: for each rang block r^i find an optimal domain block d^j, which can better minimize collage error [], using the following formula.

$$E(r^i, d^j) = \left\| r^i - (s^i \tau^n d^j + o^i 1) \right\|_2^2 \qquad (3)$$

Where $i = 1,\ 2\ ,.....\ N_r$ (N_r the number of the range block), $j = 1,\ 2,\ ....\ N_d$ (N_d the number of the domain block); s^i, o^i are respectively the brightness (luminance), and the offset factor of contrast; and 1 is the block with intensity 1 at every pixel [16, 6]. To ensure the convergence of the decoding, scaling factor is restricted to the interval $0 < s^i < 1$. Here, $\tau(r^i) \in \{\tau^1, \cdots, \tau^8\}$ is the associate affine isometric transform associate [16].

The computations include the pixel-by-pixel operations of rotating and shrinking, as well as least-squares fitting to determine optimal contrast and brightness factors. The encode process will be achieve by saving each tuplet $\left(r^i, s^i, \tau^i, o^i, d^j\right)$. The decode process consist by decoding the tuplet $\left(r^i, s^i, \tau^i, o^i, d^j\right)$.

Let the formula (3) be the least error between the range block and the domain block denoted by δ.

Fractal processing theory can be definite likes this; for r^i find d^j that minimizes the following objective equation:

$$E\left(d^j, r^i\right) = \min_{i,j}\left\| r^i - \left(s^j \tau^n d^j + o^j 1\right)\right\| \qquad (4)$$

The least square error, which minimized equation 4; so, it's can be written as:

$$\delta^i = \min_i \left\| r^i - \tilde{r}^i \right\| \qquad (5)$$

Where

$$\tilde{r}^i = \min_{i,n,j}(s^i \tau^n d^j + o^i 1) \qquad (6)$$

From Equation (6), the encode image I is obtain by summation of r^i:

$$I = \tilde{r}^1 + \tilde{r}^2 + ... + \tilde{r}^{N_r} \qquad (7)$$

The encode error δ should be the summation of δ^i so, decoding image will be obtained with error:

$$\delta = \delta^1 + \delta^2 + ... + \delta^{N_R} \qquad (8)$$

More δ is smaller better will be the quality of image. From the equation (4) the inverse reasoning can be done: find the optimal luminance parameter $\tilde{s}^i, \tilde{o}^i$, τ^n to minimize the collage error.

$$\left(\tilde{s}^i, \tilde{o}^i\right) = \min_{i,n,j\in R}\left\| r^i - \left(s^i \tau^n d^j + o^i 1\right)\right\| \qquad (9)$$

The resulting coefficients are quantized and the code-book block that yields the smallest error is chose.

III. Hybrid Fractal RANSAC theory

In fractal theory the encode image is obtained by making the summation of encode ranges blocks. The disadvantage of this method is that the quality of encoded image depends on the square error. And the partitioning of image into rang and domain block do not takes in account the edge. Although, there have been proposed new estimation methods that yield a remarkable robustness [17]. It is desirable to do the extraction, recognition and estimation without human interaction. Estimating 2D-projective homographies from grey-value templates of other features is rather instable. This paper makes a new proposal in this direction based on feature computing. The quality of the estimation of homographies depends on the mutual positioning of the corresponding features. For efficient segmentation we use object recognition techniques based on invariant local features to select matching images; which are geometrically invariant under similarity transforms and invariant under affine changes in intensity. This is done by matching features used an approximate nearest neighbour algorithm [12, 18]. For each range and domain block we compute the feature. We define f_{r^i,d^j} the mean square difference between the predicted feature locations for r^i and the candidate domain d^j by:

$$f_{r^i,d^j} = \left\| r^i - d^j \right\|^2 \qquad (10).$$

Where

$$r^i = \sum_{\substack{i=1\\j=1}}^{\substack{i=r_l\\j=r_L}} r_{i,j} \text{ and } d^j = \sum_{\substack{i=1\\j=1}}^{\substack{i=d_l\\j=d_L}} d_{i,j} \qquad (11)$$

In equation (11) the parameters r_l, r_L the size of range block and d_l, d_L the size of domain block.

IV. Error Optimization

The segmentation algorithm is posed as an optimization problem, and maintains an iteratively re-weighted least squares approximation of encoding image using direct pixel measurements. To facilitate autonomous operation, we include an algorithm for robust detection of significant planes in the environment. [14, 19, 20]. Typically, the model parameters estimated by RANSAC are not very precise. Therefore, the estimated model parameters are recomputed by for example a least-squares to the data subset which supports the best estimate. So we substituted to fractal RANSAC algorithm a fuzzy. The strength of the algorithm is that we compute at least one set of range block using equation 6, which consists only of inliers and thus results in a good estimate of the model parameters. For the estimation of fuzzy parameters we used Gauss function; which has become the scientific standard approach known as LMSE(Least Mean Square Error) [14, 22]. Moreover, LMSE will be the only correct optimal choice if the distribution of the errors is a continuous and differentiable entity [21].

We define a Gauss function $\partial(\cdot)$ which transform each δ^i into a fuzzy parameter between 0 and 1. Ideally, ∂ would be the unit step function centred at the origin. Instead the "softer" sigmoid function is used,

$$\partial\left(f_{r^i,d^j},\delta_i\right)=\frac{1}{1+e^{-f_{r^i,d^j}\delta_i}} \quad (12)$$

Small values of f_{r^i,d^j} ,δ^i result in a smooth cost function for which a rough estimate of the optimal solution can be computed. This solution, which has a better chance of being closer to the global maximum than any other arbitrary guess, serves as the initial estimate for subsequent iterations will result in the emergence of the finer details of the cost function, with the hope that a more accurate estimate will eventually be obtained.

Based on equation 12, we definite the following fuzzy parameters $\partial(\cdot)$ respectively for contrast. We defined only three values *High, Medium, Small* to build the algorithm and the fuzzy rules used for the algorithm.

V. Algorithm

For RANSAC algorithm we construct a particular set of features, a feature is first selected at random and is included in the set. The nearest feature to the set is found, and with probability p, where p is a function of feature. The next nearest feature is then selected, and the process repeats until n features. Initially we make hypotheses, which are generated by taking random samples of sets of features, and using those to compute structure estimates.

The control parameter p is set according to knowledge about the proximity of features that come from the same plane in the scene. The parameter n has to be greater than or equal to the number of features required to constrain the problem.

We use the following fuzzy algorithm to encode the image (i.e. the candidate range block):

1) If f_{r^i,d^j} is *Small* use equation 4

2) If f_{r^i,d^j} is *Medium* Make a second partition and used the following algorithm.

- If f_{r^i,d^j} still *Medium* or High used RANSAC algorithm and compute $\widetilde{s}^i,\widetilde{o}^i$ (equation 9) then use equation 4 to compute the optimal candidate range block
- If f_{r^i,d^j} *Small* use equation 4

3) If f_{r^i,d^j} High Make a second partition and used the following algorithm.

- If f_{r^i,d^j} is *Small* used equation 4
- If f_{r^i,d^j} is *Medium* use RANSAC algorithm and compute $\tilde{s}^i,\tilde{o}^i$ (equation 9) then use equation 4 to compute the optimal candidate range block
- If f_{r^i,d^j} is *High* make third partition and used the following algorithm.
    - if f_{r^i,d^j} is *Small* use equation 4
    - If f_{r^i,d^j} is *Medium* use RANSAC algorithm and compute $\tilde{s}^i,\tilde{o}^i$ (equation 9) then use equation 4 to compute the optimal candidate range block
    - If f_{r^i,d^j} is *High* use RANSAC algorithm and compute $\tilde{s}^i,\tilde{o}^i$ (equation 9) then use equation 4 to compute the optimal candidate range block

The result of or simulation has been represented in following figure.

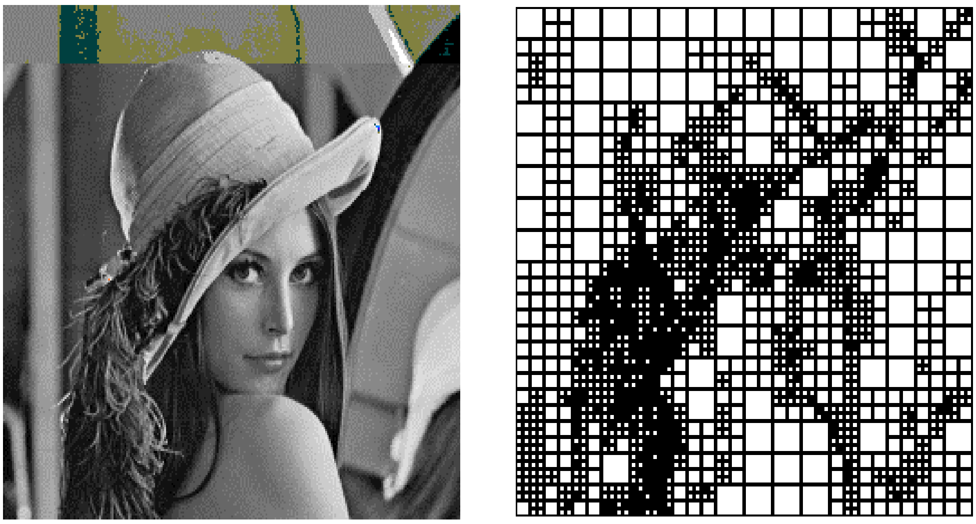

Figure 1 image processing using the proposed method

V. Conclusion

The propose method used three concepts: fuzzy, Fractal theory and RANSAC algorithm for image patterns of object to better model the underlying unknown distribution. The scheme gives good detection results on real images, even on fairly complicated scenes. The method is also reasonably robust. The computational complexity of the proposed method is moderate. The method does not require any a priori information about the site but is amenable to augmentation with contextual information. The proposed approach is quite general in nature and has potential applications to other pattern recognition tasks.

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