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Motion Estimation Using the Gradient Method by Genetic Algorithm

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***Abstract*— In this paper, we present a method to estimate the special points with the most motion in two neighbor frames. We propose a solution to determine the best illumination of either a static object, and a moving camera, either or a moving object and a static camera with two different issues: maximizing the brightness of the scene and maximizing the contrast in the image. The role of gradient estimation in global optimization is investigated. In this way, we solve the estimation of the points' motion under pixel preciseness by Genetic Algorithm in proposed image. This method shows good experimental results.**

Keywords- Genetic Algorithm; special points; estimation; motion estimation; gradient; global optimization

I. INTRODUCTION

To calculate the camera's movement, the picture's motion should be analyzed. The basic method for this purpose is using two or more frames, and finding the match points between these frames. It should be noted that for all methods, assuming equal movement for limited fields is essential.

To estimate the motion of a binocular stereo system and recover the scene structure in the form of a depth map directly from the measurements of image gradients and time derivatives in closed-form described in [1]. Presenting a method to ensure correct viewing or illumination of an object using a visual servoing scheme and only luminance or gradient information have been proposed in [2]. Describing a probabilistic formulation of the gradient, approaches to the optical flow problem. The resulting solution is an extension of the standard gradient solution [3]. Shortcoming, a region shape prediction algorithm [4] was proposed, which predicts arbitrary region shapes in the current frame by identifying their counterpart in the previous frame and sending the motion parameters.

To stabilize region shape prediction, regions are obtained from a recently proposed multi-scale segmentation transform. The proposed algorithm includes selection of the segmentation scale and assignment of motion parameters to each predicted region, and then involving the refinement of motion field using Wiener based pel-recursive motion estimation/compensation, and linear causal models [5, 6]. A novel method is introduced to deal with occluded regions which normally degrade the performance of region based techniques, and employing recursion and linear prediction methods to fine tune region estimation [7]. A commonly used class of motion estimation techniques is represented by spatiotemporal gradient approaches [8].

Another heuristic approach is to use some assumptions on the statistical property of the image gradients' distribution to either approximate the unblurred image, or to check the property of selected blurred edges to estimate the local blurring filters. Most available techniques of restoring a single blurred image assume uniform velocity motion between the camera and the scene [9]. Gradient estimation with large kernels at any image location yields better estimations due to more samples used in the computation [10]. Motion estimation compensation technique, however, improves its compression performance even further than just taking difference signals between successive pictures although it requires more computational burden for searching the motion vedor of each macro block in the picture. There are several kinds of methods available for motion estimation algorithm including pixel-recursive, optical flow, and block-based motion estimation [11] approach. Gradients of the denoised and enhanced image are estimated using the wavelet transform, and then the watershed transform is applied to the obtained gradient image [12].

This paper presents a gradient method to estimate the straight motions in two neighbor frames. We used Genetic Algorithm to find the points which have the most motion during a movement. The major reason of using Genetic Algorithm is improving the preciseness. The paper is organized as follows: Section II describes the motion estimation using the gradient method under pixel preciseness and expands its formulas which concludes the derivative functions for each point and the amount of movement. In Section III the motion estimation using the gradient method under pixel preciseness by Genetic Algorithm is presented. Section IV contains the experimental results on an image, and in section V the discussions and conclusions are presented.

II. MOTION ESTIMATION USING THE GRADIENT METHOD

Global optimization algorithms often search at many different resolutions. A coarse resolution search finds the most promising area of a large region, while a finer resolution search finds the local minima in a small region. In this section we discuss the challenges of searching at

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multiple resolutions and define a regional gradient that enables analysis of a multi-resolutional search. Some algorithms change the search resolution sequentially: first finding a region of attraction, then searching it locally to find that local optimum, then broadening the search again to find another region of attraction. Tabu search describes this process explicitly with the processes of 'intensification' (combining known good solutions to explore their local region), and 'diversification' (searching previously unexplored areas) [13]. Some algorithms accomplish multi-resolutional searches with a hybrid approach, combining stochastic movement for the global search and more structured gradient descent movements for honing in on optimum [14,15]. Other global optimization algorithms, such as PSO, search at different resolutions simultaneously, moving the particles toward both locally-promising and globally-promising regions.

The regional gradient is a way to capture functional trends over a region, and one expects that the regional gradient can be more helpful than the analytic gradient when searching for a global optimum.

In this section, we briefly review the principle of motion estimation using gradient method, assuming that we have a motion axes with under pixel preciseness for a special point. Imagine a box which is surrounding the special point with the length of (2w+1)×(2w+1) and imagine that the motion for all points, which are in the box, are the same. In this case with the OF gradient equation, it's possible to figure out the rate of motion. If we suppose that the rate is (δ_x, δ_y), then:

$$\delta_x \frac{\partial P}{\partial x} + \delta_y \frac{\partial P}{\partial y} = -\delta_t \frac{\partial P}{\partial t} \tag{1}$$

And then:

$$\frac{\partial P_{t-1}}{\partial x}\delta_x + \frac{\partial P_{t-1}}{\partial y}\delta_y = P_{t-1} - P_t = d \tag{2}$$

The amounts could be calculated by solving a linear equation system and so we have $D = G\Delta$ and then:

$$D = \begin{bmatrix} d(u-w, v-w) \\ . \\ . \\ . \\ d(u+w, v+w) \end{bmatrix} \tag{3}$$

$$G = \begin{bmatrix} \frac{\partial P_{t-1}(u-w, v-w)}{\partial x} & \frac{\partial P_{t-1}(u-w, v-w)}{\partial y} \\ . & . \\ . & . \\ . & . \\ \frac{\partial P_{t-1}(u+w, v+w)}{\partial x} & \frac{\partial P_{t-1}(u+w, v+w)}{\partial x} \end{bmatrix} \tag{4}$$

D and G are illumination differentials vector, and known gradient matrix respectively. So the unknown transfer vector is:

$$\Delta = \begin{bmatrix} \delta x \\ \delta y \end{bmatrix} \tag{5}$$

The above equation could be solved as bellow:

$$\Delta = (G^t G)^{-1} G^t D \tag{6}$$

III. Motion estimation using the gradient method under pixel preciseness by Genetic Algorithm

As it has been mentioned by the equations, we calculate Δ by the genetic algorithm optimization. In this paper, a_1 is the coding of the image before the motion. After a direct and reasonable motion, a_1 converts to a_2.

As it has been shown in motion estimation with gradient method, we assume that 8 points surround (u, v). for $x_1 = u$, and $x_2 = v$ it is shown in Fig.1.

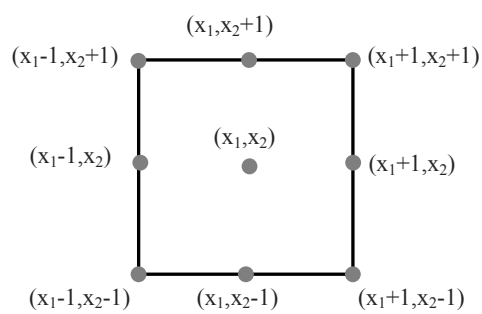

Fig. 1. Surrounding points of each pixel which have been assumed to extend the formulas

The D matrix is as follows, and $d(i)$ is the amount of the i element exchange, after the motion:

$$D = \begin{bmatrix} d(x_1+1, x_2+1) \\ d(x_1-1, x_2-1) \\ d(x_1+1, x_2-1) \\ d(x_1-1, x_2+1) \\ d(x_1, x_2+1) \\ d(x_1+1, x_2) \\ d(x_1, x_2-1) \\ d(x_1-1, x_2) \end{bmatrix} = \begin{bmatrix} a_2(x_1+1, x_2+1) - a_1(x_1+1, x_2+1) \\ a_2(x_1-1, x_2-1) - a_1(x_1-1, x_2-1) \\ a_2(x_1+1, x_2-1) - a_1(x_1+1, x_2-1) \\ a_2(x_1-1, x_2+1) - a_1(x_1-1, x_2+1) \\ a_2(x_1, x_2+1) - a_1(x_1, x_2+1) \\ a_2(x_1+1, x_2) - a_1(x_1+1, x_2) \\ a_2(x_1, x_2-1) - a_1(x_1, x_2-1) \\ a_2(x_1-1, x_2) - a_1(x_1-1, x_2) \end{bmatrix} \tag{7}$$

By using the derivative definition to equal these parameters with the numerical method we have:

$$\frac{\partial P_{(i,j)}}{\partial x_1} = \frac{P_{(i+1,j)} - P_{(i-1,j)}}{2} \tag{8}$$

$$\frac{\partial P_{(i,j)}}{\partial x_2} = \frac{P_{(i,j+1)} - P_{(i,j-1)}}{2} \tag{9}$$

With these derivative functions, we can gain the amount of the G matrix as follows:

$$G = \begin{bmatrix} \frac{a_1(x_1+2,x_2+1)-a_1(x_1,x_2+1)}{2} & \frac{a_1(x_1+1,x_2+2)-a_1(x_1+1,x_2)}{2} \\ \frac{a_1(x_1+2,x_2-1)-a_1(x_1,x_2-1)}{2} & \frac{a_1(x_1+1,x_2)-a_1(x_1+1,x_2-2)}{2} \\ \frac{a_1(x_1,x_2-1)-a_1(x_1-2,x_2-1)}{2} & \frac{a_1(x_1-1,x_2)-a_1(x_1-1,x_2-2)}{2} \\ \frac{a_1(x_1,x_2+1)-a_1(x_1-2,x_2+1)}{2} & \frac{a_1(x_1-1,x_2+2)-a_1(x_1-1,x_2)}{2} \\ \frac{a_1(x_1+1,x_2+1)-a_1(x_1-1,x_2+1)}{2} & \frac{a_1(x_1,x_2+2)-a_1(x_1,x_2)}{2} \\ \frac{a_1(x_1+2,x_2)-a_1(x_1,x_2)}{2} & \frac{a_1(x_1+1,x_2+1)-a_1(x_1+1,x_2-1)}{2} \\ \frac{a_1(x_1+1,x_2-1)-a_1(x_1-1,x_2-1)}{2} & \frac{a_1(x_1,x_2)-a_1(x_1,x_2-2)}{2} \\ \frac{a_1(x_1,x_2)-a_1(x_1-2,x_2)}{2} & \frac{a_1(x_1-1,x_2+1)-a_1(x_1-1,x_2-1)}{2} \end{bmatrix} \tag{10}$$

With these amounts which have been delivered, Δ could be found, and then we can detect the points which have the most change.

IV. Experimental results

To examine the method, as in a real picture the neighbor pixels correspond each other, it's not visible which points have the most motion. So we choose random pixels that their movements are detectable precisely. In pictures with a large scale of pixels it can't be visible which points have the most movement, so we make a square matrix which represents an image seen in Fig.2. In this paper, a_1 is a 50×50 matrix which is the coding of the image before the motion. Choosing a 50×50 matrix is an initial assumption. After making two group motions in it, as it has been illustrated in Fig.3, it's possible to analyze the picture and the points which have movement.

In these figures, it has been shown that there is a 6×6 square matrix motion, which has moved from (15,15) to (30,30), and another motion which has been proposed to move a 8×8 square matrix from (5,17) to (15,22). It should be mentioned that as there are derivative functions, the edges must be limited to calculate the optimum points. The example includes two group motions to contain the basis and the most situations which are possible in real conditions. Nevertheless if this example causes good results, we can use it for different neighbor frames.

Running the Genetic Algorithm program, the results must be the exact points which have been moved, but because of two different motions, and with different distances, the important thing for us is to find the points which have the most motion.

We tried the method by two different mutation values of 0.02 and 0.05, and the population amount of 50; the results have been shown in Fig.4 and Fig5. It's apparent that for the mutation of 0.02, as it has been shown in Fig.4, the results are the points with the motion, though it doesn't detect the most motion on a constant basis.

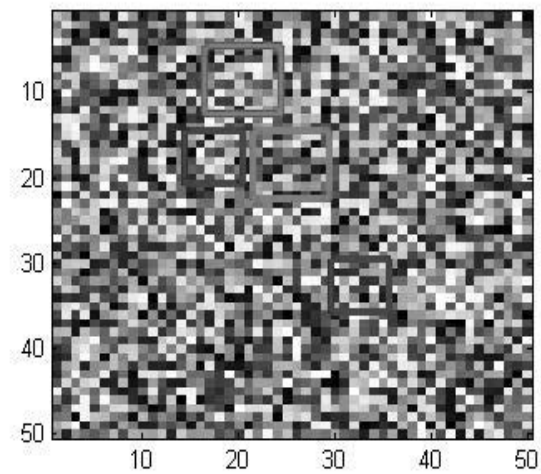

Fig. 2. The image which is equal to a1(50*50 matrix)

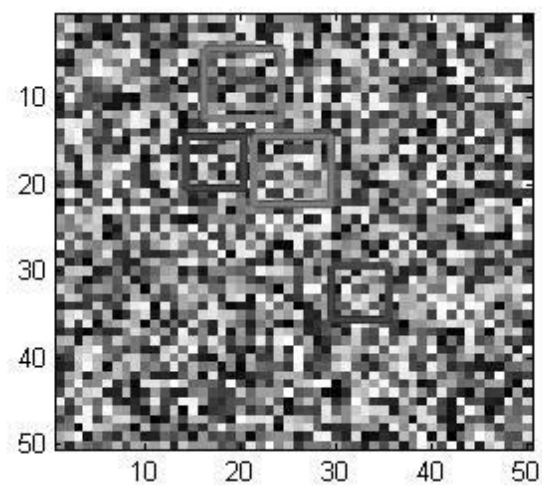

Fig. 3. The image which is equal to a2 (a1 after making two group motions in it)

Since we have two group motions in the picture, it's important to find pixels with the most movement. The Genetic Algorithm finds the points which have been moved, but because of the different values of fitness function for different points, it's important to have enough mutation in our analysis to find the different moved points. After comparing them, it's discernible that it chooses the optimum point with the best amount of fitness function.

It should be noted that sometimes it's possible to detect the most motions with a mutation rate of 0.02, but normally the result point changes between different motion's pixels, so it's not a valid rate.

In Fig.4, the result point is (10,17) which is one of the short motion group points. Although it's from the motion points, because of the 0.02 mutation, the algorithm didn't find the most motion points. In Fig. 5, the mutation is 0.05 and the result point is (33,30), which is one of the most moved points.

As the method's preciseness to find the points with the most motion is high, it's possible to use the frame with lower resolution to retrieve the calculation delay.

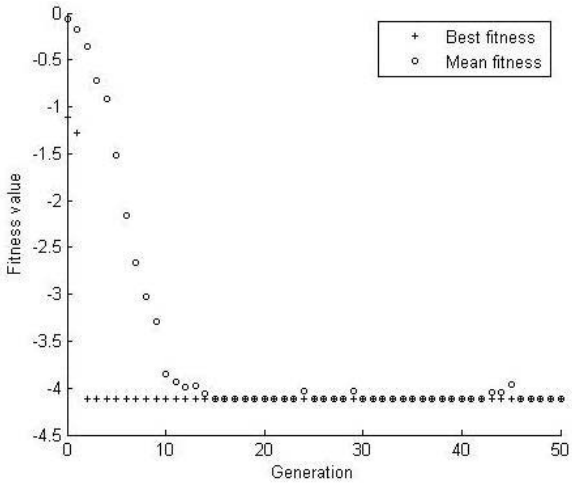

Fig. 4. Diagram of the result of the Genetic Algorithm with a Population of 50 Members and 0.02 Mutation which refers to One of the Motion's Pixels

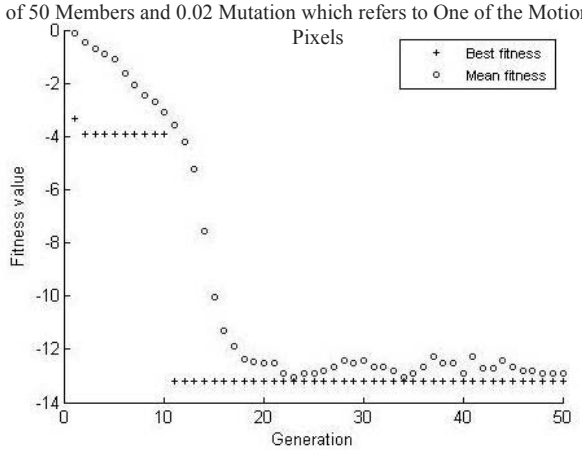

Fig. 5. Result diagram of genetic algorithm with population of 50 members and 0.05mutation which refers to one of the most motion's pixel

V. CONCLUSIONS

In this paper, we present a novel method to estimate an image motion which is one of the most important calculations of image processing. This approach uses a gradient to estimate the special points' motion values. How one can estimate the points with the most motions, has been shown experimentally.

These points, which were delivered from global optimization, are investigated for a natural image direct motion estimation which is critical. The tests give good results on images. Using the gradient method under pixel preciseness to estimate motions, it's not visible to recognize the point's with the most motion in real picture. So we don't use a real picture as an experimental example, and we study a random matrix to examine the method, and the results could be generalized to different structures. Further studies will be carried out to evaluate our algorithm performances.

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