Adaptive Local Image Registration: Analysis on Filter Size

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***Abstract*—Adaptive Local Image Registration is a Local Image Registration based on an Adaptive Filtering frame work. A filter of appropriate size convolves with reference image and gives the pixel values corresponding to the distorted image and the filter is updated in each stage of the convolution. When the filter converges to the system model, it provides the registered image. The filter size plays an important role in this method. The analysis on the filter size is done using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity (SSIM) index. Analysis shows that the convergence action of filter would negatively affect by a small increase in filter size. If the displacements between the images are large, it requires a large filter.**

Keywords-Local Image Registration, Adaptive Filtering

I. INTRODUCTION

Image registration is the process of overlaying two or more images of same scene taken at different time, from different viewpoints and or by different sensors. The major registration purpose is to remove or suppress geometric distortions between the reference and sensed images, which were introduced due to different imaging conditions, and thus to bring images into geometric alignment.

Local image registration methods employ local domain of transformation [4] and it can handle spatially varying deformations. The important Local Image Registration methods are Adaptive Local Image Registration [1]-[3], Dense motion estimation methods [5]-[7], 2-D mesh based approaches [8] and Methods employing a 3-D scene representation [9].

'Adaptive Local Image Registration' is based on adaptive filtering frame work [10]. Since Adaptive filters can estimate unknown systems and can track smooth changes in the system, this method register the images without the explicit estimation of the local displacement. Space-filling curves [11] such as Hilbert curve is used to get spatial contiguity in images and for mapping 2-D image into a 1-D update sequence. Here an adaptive filter convolves with reference image and gives the predicted pixel value for the current pixel value of the distorted image. This is known as prediction step. After this the error between the predicted output and the distorted image is calculated and using this error and previous filter parameter, the filter is updated. When the filter converges to the system model, it provides the registered image. To preserve the contiguity the Hilbert curve scanning order is used here. This method can be used for both gray scale and colour images.

Filter size plays an important role in the result of the Adaptive Local Image Registration. Filters of different size for different distortion angles in the same set of images are used to analyze the effects of filter size in the result of the Adaptive Local Image Registration. The quantitative performance evaluation is done using Mean Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity (SSIM) index. Analysis shows that the convergence behavior would adversely affect by a small increase in filter size and if the displacements between the images are large, it requires a large filter.

Adaptive Local Image Registration method is presented in Section 2. Section 3 discusses the analysis on filter size and conclusion is presented in Section 4.

II. ADAPTIVE LOCAL IMAGE REGISTRATION

If we have two images $I_1(x, y)$ and $I_2(x, y)$ such that the spatial coordinates of one image locally distorted with respect to the other, usually the relation between the two images, over the region of overlap, is represented by

$$I_2(x, y) = I_1(x + d_x(x, y), y + d_y(x, y)) \quad (1)$$

where $d(x, y) = (d_x(x, y), d_y(x, y))$ is a subpixel-valued spatially varying displacement field. So the image registration problem is the estimation of this spatially varying subpixel displacement field and mapping of image $I_2(x, y)$ on to the coordinate system of image $I_1(x, y)$.

In Adaptive Local Image Registration, local image distortions between $I_1(x, y)$ and $I_2(x, y)$ by means of a spatially varying linear filter $h_0(x, y; x_{0,} y_0)$, over the region of overlap as

$$I_2(x_0, y_0) = \sum_{x,y} h_0(x, y; x_0, y_0) I_1(x, y) + e(x_0, y_0) \quad (2)$$

It is required to determine the system response $h_0(\cdot)$ to map image $I_2(x, y)$ onto the coordinate system of image $I_1(x, y)$. By using an adaptive filtering framework, the proposed method estimate $h_0(x, y; x_{0,} y_0)$ without explicitly estimating the sub pixel-valued local displacement field $d(x, y) = (d_x(x, y), d_y(x, y))$. This can be implemented in two ways as Pixel-by-Pixel Method and Block-Based Method.

A. *Pixel-By-Pixel Method*

An adaptive filtering framework can be extended to image registration problem based on the model of eqn(2). Adaptive Filtering consists of a two step process: 1) a filtering step, where the filter coefficients, $\hat{h}(x, y; x_{0,} y_0)$ are convolved with the input image, $I_1(x, y)$ to produce an estimate of the desired response, $I_2(x, y)$, and 2) an adaptive process where the set of filter coefficients are adjusted using the resulting estimation error, $e(x, y)$. The LMS adaptation algorithm is used as the update algorithm in Adaptive Filtering. The entire process can be expressed by the following algorithm.

Algorithm

1) Prediction step

$$\hat{I}_2(x_0, y_0) = \sum_{(x, y \in R)} \hat{h}_b(x, y; x_0, y_0) I_1(x, y) \quad (3)$$

where $\hat{h}_b$ *is the 2-D adaptive filter and* I_1 *is the reference image.*

2) Error estimation step

$$e(x_0, y_0) = I_2(x_0, y_0) - \hat{I}_2(x_0, y_0) \quad (4)$$

where I_2 *is the distorted image.*

3) Filter updattion step

$$\hat{h}_a(x, y; x_0, y_0) = \hat{h}_b(x, y; x_0, y_0) + \beta e(x_0, y_0) I_1(x, y)$$
$$\forall (x, y) \in R \quad (5)$$

where R *is the support of the filter, and* β *is the* *adaptation step-size.*

4) Initializing the filter for the next pixel

$$\hat{h}_b(x, y; x_n, y_n) = \hat{h}_a(x, y; x_0, y_0),$$
$$\forall(x, y) \in R \qquad (6)$$

where the subscripts b and a denote before and after adaptation, respectively.

When the adaptive filter $\hat{h}(x, y; x_{0,} y_0)$ converges to the system model $h_0(x, y; x_{0,} y_0)$ and tracks changes in the system model, then the algorithm above provides a method for registering one image to another. β denote the adaptation step-size it determines the speed of convergence, tracking capability, and the closeness of the approximation. Fig 1 gives the overview of adaptive filtering for images.

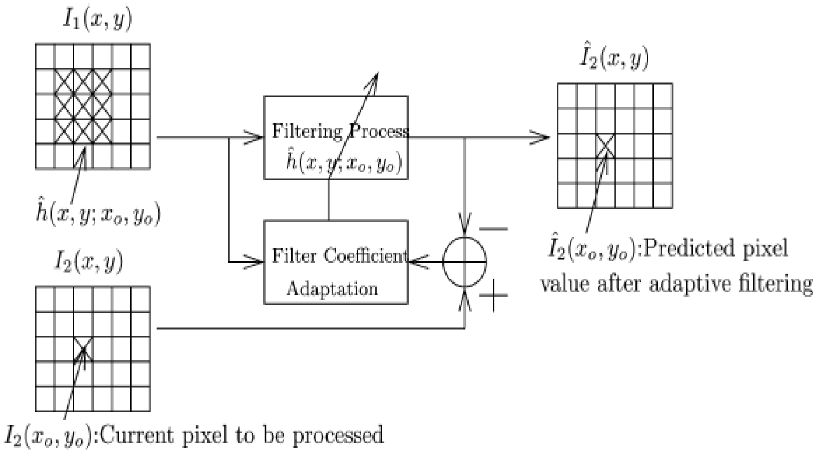

Fig 1 Adaptive Filtering of Image

B. Block Based Method

In Pixel-By-Pixel method filter coefficients may vary in unconstrained manner on a pixel-by-pixel basis. In this situation the current pixel information in the update step yields infinitely many solutions to the system identification problem. To overcome this problem, regularization approaches are needed. In Block-Based method, regularization by block based adaptation of the coefficients is implemented. Here system response is assumed to remain constant over a block of pixels around the current pixel.

For this, a new optimization criterion, $E_{B_0}(x_{0,} y_0)$, which is the sum of estimation errors $e(x, y)$ over a block B_0 of pixels is defined.

$$E_{B_0}(x_{0,} y_0) = \sum_{(x_b, y_b) \in B_0} e^2(x_b, y_b) \qquad (7)$$

where B_0 is the block around the current pixel, $I_2(x_{0,} y_0)$. When integrate the prediction step and error estimation step of LMS algorithm with eqn(7) will be modified as follows

Algorithm

1) Prediction step

$$\hat{I}_2(x_0, y_0) = \sum_{(x, y \in R)} \hat{h}_b(x, y; x_0, y_0) I_1(x, y) \qquad (8)$$

where $\hat{h}_b$ *is the 2-D adaptive filter and* I_1 *is the reference image.*

2) Optimization criterion estimation step

$$E_{B_0}(x_0, y_0) = \sum_{(x_b, y_b) \in B_0} \left(I_2(x_b, y_b) - \sum_{(x_i, y_i) \in R_b} \hat{h}_b(x_i, y_i; x_0, y_0) I_1(x_i, y_i) \right)^2 \quad (9)$$

where E_{B_0} *is the sum of estimation errors* $e(x, y)$ *over a block* B_0 *of pixels and* I_2 *is the distorted image*

3) Filter updattion step

$$\hat{h}_b(x_i, y_i; x_b, y_b) = \hat{h}_b(x_i, y_i; x_0, y_0) + \beta \sum_{(x_b, y_b) \in B_0} \left(I_2(x_b, y_b) - \sum_{(x_i, y_i) \in R_b} \hat{h}_b(x_i, y_i; x_0, y_0) I_1(x_i, y_i) \right) \times I_1(x_{ib}, y_{ib}) \quad (10)$$

where β *is the adaptation step-size.*

4) Initializing the filter for the next pixel

$$\hat{h}_b(x_i, y_i; x_n, y_n) = \hat{h}_a(x_i, y_i; x_0, y_0), \quad (11)$$

where the subscripts b *and* a *denote before and after adaptation, respectively.*

When the adaptive filter $\hat{h}_b(x, y; x_0, y_0)$ converges to the system model $h_0(x, y; x_0, y_0)$ and tracks changes in the system model, then the algorithm above provides a mechanism for registering one image to another. Here the updated adaptive filter coefficients $\hat{h}_a(x_i, y_i; x_0, y_0)$ are computed by taking the derivative of $E_{B_0}(x_0, y_0)$ with respect to the filter coefficients. Block-Based Method shows better performance than Pixel-By-Pixel method.

III. ANALYSIS ON FILTER SIZE

Filter size plays an important role in the result of this method. An optimum filter size should be selected for good performance. The quantitative performance evaluation is done using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity (SSIM) index. Fig 2 shows the results table 5.2 represents the performance of method obtained using different window size for different distortion angle.

(a) (b) (c)

(d) (e)

Fig 2.Results of Adaptive Local Image Registration (a) Reference image, (b) Distorted(input) image, (c) Difference of (a) and (b), (d) Registered image (e) Difference of (a) and (d)

High PSNR and the SSIM index nearer to one shows good performance. To analyse the variation of performance with filter size a gray scale image(Cameraman) of size 256 X 256 as the original (reference) image and 8-bit gray scale image of size 256X256 with geometric distortion as the input image are tested with filter sizes 3 X 3, 5 X 5, 7 X 7, 9 X 9, 11 X 11 and 13 X 13 for distortion angles 2^0, 4^0, 6^0 and 8^0. PSNR and SSIM of each test is given in table 1. From the table 1, it is seen that a 5X5 filter gives better performance for distortion angle 2^0, for distortion angles 4^0 and 6^0 a 9X9 filter is optimum and a 13X13 filter is good for distortion angle 8^0. So by analyzing the table 1 it is clear that a small increase in filter size negatively affects the convergence behaviour. It also increases computational complexity. If the displacements between the images are large, it requires a large filter. Because the size of the adaptive filter should be capable to act as the spatially varying system model $h_0(x, y; x_{0,} y_0)$ at each point.

TABLE I. PERFORMANCE ANALYSIS TABLE

Distortion Angle	2^0		4^0		6^0		8^0	
Filter Size	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
3 X 3	21.98	0.945	21.46	0.939	19.90	0.915	17.82	0.869
5 X 5	24.26	0.960	22.19	0.949	22.73	0.955	22.59	0.953
7 X 7	24.18	0.960	22.82	0.955	22.87	0.956	22.85	0.955
9 X 9	24.07	0.958	23.12	0.957	22.99	0.957	22.93	0.956
11 X 11	23.95	0.957	23.10	0.956	22.80	0.956	23.05	0.957
13 X 13	23.88	0.954	23.04	0.951	23.76	0.954	23.01	0.956

IV. CONCLUSION

Filter size plays an important role in the result of the Adaptive Local Image Registration. The effects of filter size is analyzed using the filters of different size in the same set of images and also for different distortion angles in the same set of images. The quantitative performance evaluation is done using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity (SSIM) index. Analysis shows that the convergence behavior would negatively affect by a small increase in filter size and large filters are required if the displacements between the images are large.

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