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A Robust Technique for Feature-based Image Mosaicing using Image Fusion

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Abstract

Since last few decades, image mosaicing in real time applications has been a challenging field for image processing experts. It has wide applications in the field of video conferencing, 3D image reconstruction, satellite imaging and several medical as well as computer vision fields. In this paper, we have proposed a feature based image mosaicing technique using image fusion. Initially, the input images are stitched together using the popular stitching algorithms i.e. Scale Invariant Feature Transform (SIFT) and Speeded-Up Robust Features (SURF). To extract the best features from the stitching results, the blending process is done by means of Discrete Wavelet Transform (DWT) using the maximum selection rule for both approximate as well as detail-components. The SIFT provides scale as well as rotational invariance property. The SURF provides better computation speed and illumination invariance. The robustness and quality of the above mosaicing techniques are tested by means of three-dimensional rotational images.

Keywords

Mosaicing, Panorama, Image Fusion, SIFT, SURF, DWT.

1. Introduction

Virtual Environment and panoramic imaging has been an emerging field of research with the improved brain-computer interfacing to deal with real-time applications. Image mosaicing plays a vital role in developing the panoramic view. The complementary information of individual image scenes in spatial and temporal domain can be combined to produce unsegmented panorama using images of smaller field of view. A number of image mosaicing algorithms have been proposed to generate a seamless, wide view image to interpret real world more clearly. In this paper, we proposed a robust technique for panoramic image mosaicing by means of image fusion. The proposed technique consisting of two efficient stitching algorithms i.e. SIFT and SURF. The SIFT algorithm performs better for images with scale and rotational variance. These properties compensate the requirement of SURF. Again, the SURF is known for its illumination invariance and better computational speed. The response of both is blended together using the optimum image fusion rule. Here, the fusion process takes place using Haar Discrete Wavelet Transform (DWT).

2. Literature Review

Image stitching algorithms can be categorized into two broad horizons. The first is the direct method [1, 2] and the second one is based on image features [3, 4]. The direct methods need an ambient initialization, whereas, feature based methods do not require initialization during registration [5]. The feature-based techniques are primarily consisting by the four steps: feature detection, feature matching, transformation model estimation, image resampling and transformation [6]. In 2004, David G. Lowe proposed an algorithm known as Scale Invariant Feature Transform (SIFT), which is considered as a feature-based method invariant to scale, rotation as well as affine transformation [7]. In 2006, Herbert Bay developed a Speeded-Up Robust Features (SURF) algorithm [8]. It is mostly used for real-time applications. Again, the image fusion job for multi-sensor images at an altering resolution can be fruitfully implemented by means of wavelet based Multi Resolution Analysis (MRA) [9]. The review paper by S. Krishnamoorthy et al.[10], Haar wavelet transform fusion technique has been appraised as the salient method especially for subjective analysis. This paper is organized in the following manner. In section-II, the proposed image mosaicing technique is depicted. The simulation results are vividly discussed in section-III. Finally, the paper is concluded with the highlights of the proposed technique in section-IV.

3. Proposed method

The proposed method mainly consists of the following major steps:

i. Concerned image acquisition
ii. Image stitching algorithms
iii. Image fusion

The flow chart for the proposed methodology is shown below:

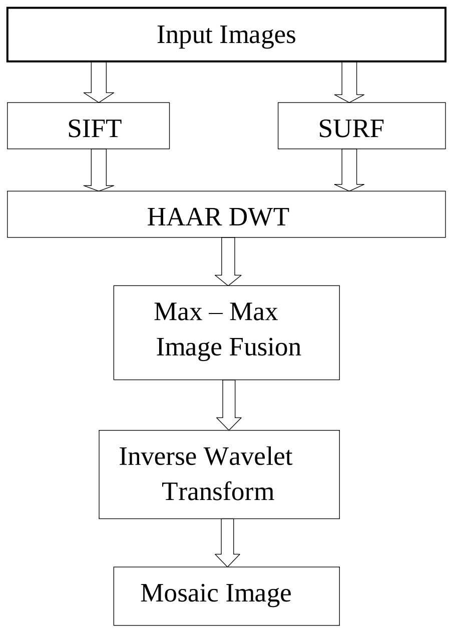


Fig.1: Flow chart for proposed technique

A. SIFT

Lowe proposed a scale invariant feature transform algorithm [11] in the year 1999. It has the unique features, such as rotation, affine transformation, scale invariance and noise immunity. SIFT algorithm is based on feature spotting in scale space. The four major steps of this algorithm are:

(1) Scale space detection[12], preliminary confirm the key points, location and the scale as shown in Fig.2 The middle point is compared with its neighbourhood points to detect utmost points.

(2)Using Taylor expansion, the extreme points and location are carefully determined using the following equation:

$$D(x) = D + \frac{\partial D^T}{\partial x} x + \frac{1}{2} x^T \frac{\partial^2 D}{\partial x^2} x$$

(1)

(3) By the help of key point neighbourhoods, the gradient m (x, y) and the direction are estimated for an image L(x, y). The gradient and direction can be formulated as:

$$m(x,y) = \sqrt{(L(x+1,y) - L(x-1,y))^2 + (L(x,y+1) - L(x,y-1))^2}$$

(2)

$$\theta(x,y) = \arctan\left(\frac{L(x,y+1) - L(x,y-1)}{L(x+1,y) - L(x-1,y)}\right)$$

(3)

Taking the gradient value and characteristic into consideration, each sample points is added to the histogram. The direction for the feature points are estimated from the maximum peak values from the histogram.

(4) Feature vectors [13] are generated, which is shown in Fig.3. The arrow in each cell stands for gradient direction along with the amplitude of pixels. The seed point can be formed by aligning the unidirectional gradients followed by the normalization.

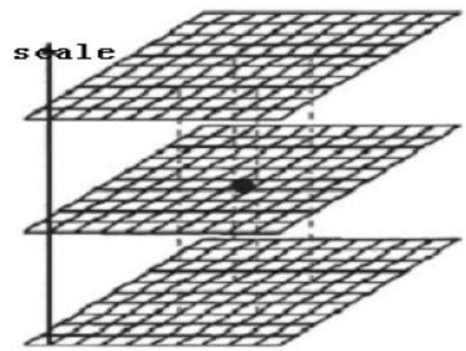


Fig. 2: Local extremum in DoG scale space

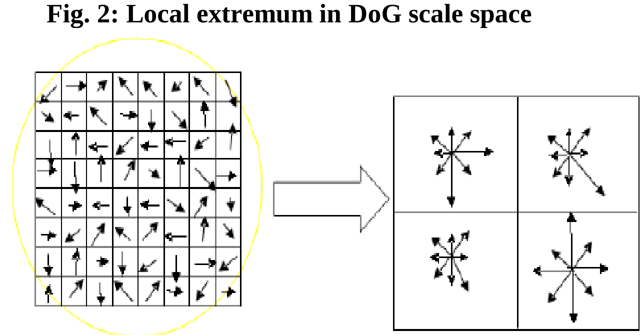


Fig. 3: Feature vector generation

B. SURF

A Speeded-Up Robust Features based algorithm [8] developed by Herbert Bay in 2006. It became popular for its computing speed. This algorithm is also based on scale space theory. Without down sampling, it generates a stack in order to restore the same resolution. Here, the local maxima are estimated using Hessian matrix (H). The Hessian matrix of an image at any point $X = (x, y)^T$ is

$$H(x,\sigma) = \begin{pmatrix} L_{xx}(x,\sigma) & L_{xy}(x,\sigma) \\ L_{xy}(x,\sigma) & L_{yy}(x,\sigma) \end{pmatrix}$$

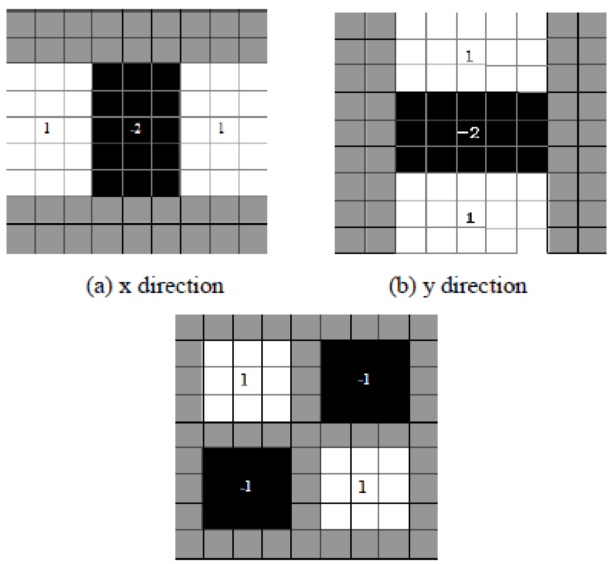
(4)

Where, $L_{xx}(x,\sigma)$ represents the convolution of middle point X with the Gaussian filter $\frac{\partial^2 g(\sigma)}{\partial x^2}$

To enhance the computing speed, the box filter approximation is taken instead of Gaussian filter. The multi-directional box filters are shown in Fig.4. The determinant of Hessian matrix, ΔH can be reduced to

$$\Delta H = D_{xx} D_{yy} - (w D_{xy})^2 \quad (5)$$

`The response for each spot can be determined by assigning ω = 0.9 [8]. A threshold is set for non-maxima suppression to detect the extreme points. The stable feature points are chosen by comparing with the neighbouring values followed



(a) x direction (b) y direction

(c) xy direction

Fig.4: Multi-directional box filters

by the interpolation operation in scale space. Gaussian weighting coefficients are merged with Haar wavelet responses to extract the interest points. The Haar wavelet responses in vertical direction (dy) and in horizontal direction (dx) are summed up along with the absolute value of the response as:

$$\text{Vsub} = (\Sigma dx, \Sigma dy, \Sigma|dx|, \Sigma|dy|) \quad (6)$$

The normalized description vector helps to combat with illumination variance.

C. Image fusion

Image fusion is the process in which two or more images are blended together to form an image holding all the common as well as complementary information from each of the original images. The fusion process also produces a higher spatial resolution image free from all volatile blurring effects. Pixel level image fusion techniques are mostly stirred by blurring effect and usually time consuming due to large number of computations. So, in this paper, we have opted for wavelet base multi resolution analysis technique mitigating all issues due to pixel level fusion. The original image is passed through high pass and low pass filters so as to get the detail and approximate components. Again, the down sampling operation takes place followed by the next filtering stage to generate the low-low (LL), low-high (LH), high-low (HL), high-high (HH) image sub band components. Here, we have implemented the Haar-wavelet decomposition for better subjective analysis [10]. The discrete wavelet based decomposition process flow is shown in Fig.5.

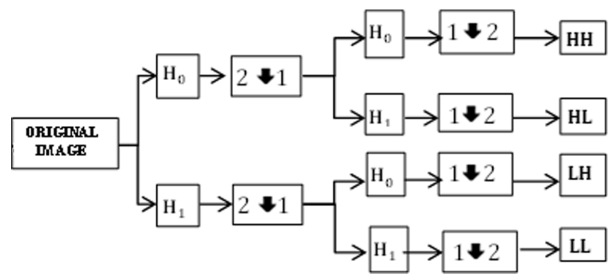


Fig.5: Discrete wavelet decomposition with filter banks

The unique features of Haar wavelet transform are its excellent processing speed, simplicity, memory management as well as reversibility. The subjective performance analysis of some of the popular wavelets is shown in Fig.6. The Haar mother wavelet function $\psi(t)$ can be presented as:

$$\psi(t) = \begin{cases} 1 & 0 \le t \le 0.5 \\ -1 & 0.5 \le t \le 1 \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

The scaling function $\phi(t)$ is given by

$$\phi(t) = \begin{cases} 1 & 0 \le t \le 0.5 \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

The lower order Haar matrix is

$$H_2 = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \tag{9}$$

The decomposed coefficients can be integrated using inverse discrete wavelets transform (IDWT). The fusion rule for this process is Maximum selection scheme to extract only the dominant sub-band components. The generalized discrete wavelet based image fusion process flow is depicted in Fig.7. The fusion of responses from scale invariant feature transform algorithm and speeded-up robust features based algorithm regenerates an panoramic image having the best features of both the algorithms. The resultant image is robust towards rotation, noise as well as illumination invariant photography.

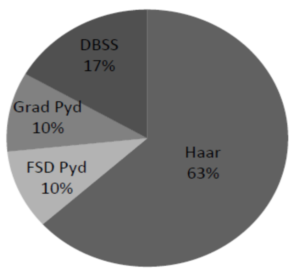


Fig.6: Subjective analysis of DWTs [10]

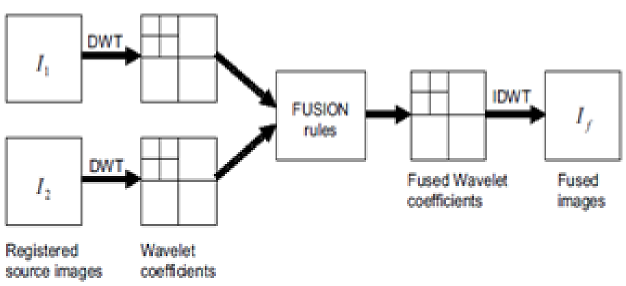


Fig.7: DWT based Image Fusion Flow chart

4. Performance evaluation

Both objective as well as subjective performance evaluation has been a crucial part of image quality evaluation process. Here, the simulation resultant image quality are verified in terms of PSNR, Feature Similarity Index (FSIM), Mutual Information (MI), Normalized Absolute Error (NAE) and Standard Deviation (SD).

i. PSNR as Quality Measure

The peak signal-to-noise ratio (PSNR), in decibels is calculated between the reference and processed image. The more the PSNR, the better the quality of the reconstructed image. PSNR can be calculated by using the following equation:

$$PSNR = 10\log_{10}\left(\frac{R^2}{MSE}\right) \tag{10}$$

Where, R is the maximum range in the input image data type.

ii. FSIM as Quality Measure

For Combined similarity

$$S_L(x) = [S_{PC}(x)][S_G(x)]$$

and $PC_M(x) = \max(PC_1(x), PC_2(x))$

$$FSIM = \frac{\sum_{x\in\Omega} S_L(x).PC_M(x)}{\sum_{x\in\Omega}.PC_M(x)} \tag{11}$$

Where, Ω means the whole image spatial domain.

iii. **Mutual Information (MI)**

It measures the asymmetry between the two desired images as well as the fluctuation from its mean value. MI for two images M (i, j) and N (i, j) can be expressed as

MI = H(M) + H(N) - H(M,N) (12)

Where. H(M) is the entropy of image M(i, j), H(N) is the entropy of image N(i, j) and H(M, N) is the joint entropy of image M(i, j) and N(i, j).

iv. Enhancement performance measure (EME)

It is a quantitative method to measure the image enhancement. In terms of entropy it can be defined with the help of an image, which is divided into k1k2 blocks $w_{k,l}(i, j)$

$$EME = \min_{\phi\in\{\phi\}}(EME(\phi))$$

$$= \min_{\phi\in\{\phi\}}\left(\frac{1}{k_1k_2}\sum\sum 20\log\frac{I^w_{\max;k,l}(\phi) - I^w_{\min;k,l}(\phi)}{I^w_{\max;k,l}(\phi) + I^w_{\min;k,l}(\phi)}\right) \tag{13}$$

Where, $I^w_{\max;k,l}(\phi)$ and $I^w_{\min;k,l}(\phi)$ are maximum and minimum of image X (n1, n2).

v. Normalized Absolute Error (NAE)

The Normalized Absolute Error can be used for image quality metric and formulated as

$$NAE = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(\left|A_{ij} - B_{ij}\right|\right)}{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(A_{ij}\right)} \quad (14)$$

Where, A- perfect image and B- fused image to be assessed. The image fusion result is appreciable with respect to subjective analysis. The objective evaluation of the fused image is depicted in Table.1.

Table.1: Performance Analysis

Algorithm/ Parameters	SIFT	SURF	Proposed
PSNR (dB)	41.693	41.962	42.415
FSIM	0.706	0.714	0.739
MI	1.209	1.264	1.465
EME	8.561	6.332	9.457
NAE	0.147	0.143	0.132
SD	56.846	56.542	57.283

5. Results & Discussion

In the proposed technique, the two test images are acquired by means of a camera DSC-WS70, maximum aperture of 2.75, focal length of 14 mm and exposure time of 0.02 sec. The unique feature of the images is that, these are three dimensional rotational images. Here, we have captured the two images at rotational angle of 10º. The input images are shown in Fig.8 and Fig.9. The images also have some illumination variation. The ground truth image has been generated using Autostitch software. The images are processed through scale invariant feature transform and speeded-up robust features algorithms separately in a parallel process. The response of SIFT and SUFT algorithms are shown in Fig.10 and Fig.11 respectively. The panoramic images generated from these algorithms are passed through the blending process using the Haar discrete wavelet transform. The wavelet decomposition tree is presented in Fig.12. Here, we have implemented the maximum-approximate and maximum-detail fusion rule to generate a panoramic image of high contrast, robust towards noise as well as illumination variation. The fused panoramic image is depicted in Fig.13. Here the panoramic image generated by the fusion process compensates the complementary features and boosts up the common features of individual stitching images. SURF algorithm has the distinctive property of illumination invariance along with good scale and rotational invariance property, whereas, SIFT is more effective algorithm for scale and rotational image stitching [14]. But, it cannot cope up with illumination variation. Therefore, the resultant image proves superior as compared to the SIFT as well as SURF algorithms in terms of PSNR, Mutual Information (MI), Normalized Absolute Error (NAE), Feature Similarity Index Metric (FSIM), Standard Deviation (SD) and Measure of Enhancement(EME).

Fig.8: Input image-I

Fig.9: Input image-II

Fig.10: SIFT response

Fig.11: SURF response

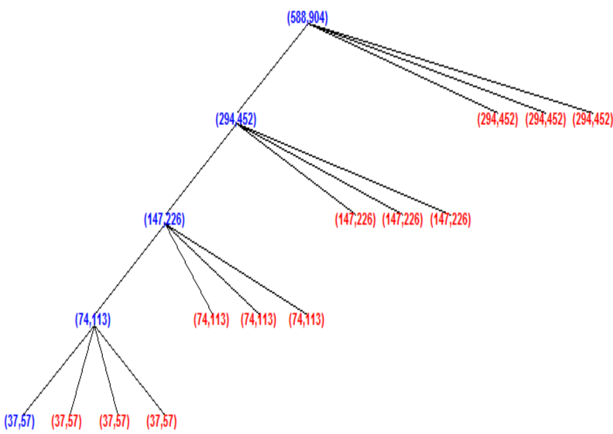


Fig.12: Haar Wavelet decomposition tree at 4th level

Fig.13: Fused image

6. Conclusions

In this paper, we proposed a novel panoramic image mosaicking technique for three dimensional, rotational images with illumination variation. The input images are passed through two robust stitching algorithms i.e. SIFT and SURF. The Scale Invariant Feature Transform is invariant towards scale and rotational variation. It is also robust towards noisy environment. Speeded-Up Robust Features algorithm is has very similar properties as SIFT. However, it has the properties of illumination invariance and good computational speed. Therefore, the fusion result of these two efficient algorithms gives rise to a panoramic image, which carries all the properties of both. The performance evaluation of proposed technique is done in terms of PSNR, FSIM, MI, EME, NAE and SD. The proposed method shows superior results as compared to both SIFT and SURF.

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