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Implementation of Panoramic Image Mosaicing using Complex Wavelet Packets

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ABSTRACT

Image Mosaicing is an active research area in computer vision and computer graphics. Image mosaicing is the process of combining two or more images of the same scene into one high resolution image which is called panoramic image mosaicing. Image mosaicing techniques can be categorized into two general approaches: direct and feature based techniques. Direct techniques compare all the pixel intensities of the images with each other, whereas feature based techniques aim to determine a relationship between the images through distinct features extracted from the processed images. Feature extraction is the process of extracting the invariant features from the images. Several methods were proposed earlier for the feature extraction like Harris corner detector and scale invariant feature transform (SIFT), which are difficult and time consuming for real time applications. The wavelet feature extraction is not effective because of decomposing the image into wavelet subspaces at various scales and extracting key point by decomposing low frequency coefficients to get high frequency coefficients. And also wavelets will give an orientation variant feature which is not suitable for much application like image mosaicing. To achieve a better feature extraction a novel method is introduced and implemented by using complex wavelet packets. Here the image decomposed into wavelet subspaces at various scales and extracting key point by decomposing high frequency coefficients to get high frequency coefficients. This makes feature extraction very simple and more effective at different scales to get strong key point. Implementation results show that the feature extraction by using the proposed method is more reliable for real time applications when compared with existing methods.

Key words: Image mosaicing, Feature extraction, SIFT, DWT, complex wavelet packets

INTRODUCTION

A panoramic image mosaic is a synthetic composition generated from a sequence of images and it can be obtained by understanding the geometric relation between the images [10]. The geometric relations are the coordinate system that relates the different image coordinate systems. By applying the appropriate transformation via warping operation and merging the overlapping regions of distorted images, it is possible to construct a single image indistinguishable from a single large image of the same object, covering the entire visible area of the scene. The output image is the motivation for image mosaicing. Masking can be done in three steps they are feature extraction, stitching, and blending. The majority approaches to image stitching require nearly exact overlap between images and identical exposures to produce seamless results. The direct and feature based techniques are considered as the main approaches for image mosaicing. The direct techniques work by directly minimizing pixel to pixel dissimilarities. Otherwise, the feature based techniques work by extracting a sparse set of features and then matching these to each other [11].

Features should be distinctive objects which are possibly uniformly spread over the images and without difficulty in finding these features. The identify feature sets in the original and sensed images must have enough common elements, even when images do not exactly cover the same scene. The desirable property for a feature detector is repeatability whether or not the same feature will be detected in two or more different images of the same scene. Many computer vision algorithms use feature detection as the initial step. Features are distinguishable properties, distinct areas of interest such as an edge; corner or a contour can be considered as features in an image.

Edge detection is an important task in feature extraction. An edge in an image is a contour across which the brightness of the image changes abruptly. An edge detector is basically a high-pass filter that can be applied to extract the edge points in an image. In addition to edges, the corners are also considered the best features that can be extracted from an image. Other than edges and corners, blobs are also the best candidates for extracting salient features in an image. Blobs are regions in the image that may contain objects of interest and are either brighter or darker than its surroundings. Some of the approaches employed to detect blobs are Laplacian of Gaussian (LoG), Difference of Gaussian (DoG), Determinant of Hessian etc. which are chosen appropriately for the desired application.

Harris corner detector [1] is a well-known interest key point detector due to its invariance to rotation, illumination variation. But it doesn't scale-invariant. Lowe in [2] [3], has addressed the problem of affine invariance for feature extraction and proposed the so called scale-invariant feature transform (SIFT) descriptor, that is invariant to image translations and rotations, to scale changes (blur), and robust to illumination changes, but has slow execution time.

WAVELET BASED FEATURE EXTRACTION

The wavelet is proved to be a powerful mathematical tool. It can be used in many image processing applications such as compression, image edge enhancement, and feature extraction. Wavelet transforms can decompose images into elementary building blocks that are well localized both in space and frequency. A wavelet is used to divide a given function into different frequency components. A wavelet transform [4] is the representation of a function by wavelets, which represent scaled and translated replicas of a finite length. Wavelet analysis consists of decomposing an image into a hierarchical set of approximations and details. For image analysis uses two-dimensional wavelets and corresponding scaling functions obtained from one dimensional wavelets by tonsorial producing. It decomposes the image into low and high frequency bands and analysis the information in an image with less number of coefficients. Extracting the features this method is simple and fast.

<table>
<tr><td>LL3</td><td>HL3</td><td rowspan="2">HL2</td><td rowspan="3" colspan="2">HL1</td></tr>
<tr><td>LH3</td><td>HH3</td></tr>
<tr><td colspan="2">LH2</td><td>HH2</td></tr>
<tr><td colspan="3">LH1</td><td colspan="2">HH1</td></tr>
</table>

Fig. 1 Wavelet decomposition

The above figure1 represents the process of wavelet decomposition. Apply wavelet transform on the results of row operations, but now moves column-wise starting from the left column where we use wavelet or scaling function depending on whether we want LL, LH. HL or HH components. It decomposes the image and generates low frequencies and high frequency outputs. These outputs are referred as an approximation, horizontal detail, vertical detail, and diagonal detail. First, we must get the equation for the scaling function and separable wavelet functions, so Eq. (1) Is the separable scaling function, Eq. (2) - Eq. (4) Is the separable wavelets. Here Ψ^H refers to the change along the columns which means the horizontal edges, Ψ^V is the difference along the row, which refers to the vertical edges, Ψ^D is the variation along the diagonals.

$$□(x,y)=\varphi(x)\varphi(y) \tag{1}$$
$$\Psi^H(x,y)=\Psi(x)\Psi(y) \tag{2}$$
$$\Psi^V(x,y)= \Psi(x)\Psi(y) \tag{3}$$
$$\Psi^D(x,y)= \Psi(x)\,□(y) \tag{4}$$

Now separable scaling and wavelet functions, we can assign the scaled Eq. (5) And translated basis Eq. (6) -Eq.

$$\varphi_{j,m,n}(x,y)=2^{j/2}\varphi(2^j x-m,2^j-n) \tag{5}$$

$$\psi^H_{j,m,n}(x,y)=2^{j/2}\psi^H(2^j-m,2^j-n) \tag{6}$$

$$\psi^V_{j,m,n}(x,y)=2^{j/2}\psi^V(2^j-m,2^j-n) \tag{7}$$

$$\psi^D_{j,m,n}(x,y)=2^{j/2}\psi^D(2^j-m,2^j-n) \tag{8}$$

Once we have the basis function, we can now define the discrete wavelet transform of the image which can be found at Eq. (9) - Eq. (12) where M, N, H, V, D, *W*□(*j*0*; m; n*), □ (*j; m; n*), □ (*j; m; n*), □ (*j; m; n*), represents the number of columns in the image, number of rows in the image, horizontal, vertical, diagonal, approximate coefficients at scale j_0 which is usually equal to 0, horizontal, vertical, and diagonal detail coefficients at scale j where j ¸ j_0 respectively.

$$w_{\varphi}(j_0,m,n)=\frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}f(x,y)\varphi_{j,m,n}(x,y) \tag{9}$$

$$w_{\psi}^{H}(j;m;n)=\frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}f(x,y)\psi_{j,m,m}^{H}(x,y) \tag{10}$$

$$w_{\psi}^{V}(j;m;n)=\frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}f(x,y)\psi_{j,m,m}^{V}(x,y) \tag{11}$$

$$w_{\psi}^{D}(j,m,n)=\frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}f(x,y)\psi_{j,m,n}^{D}(x,y) \tag{12}$$

After the wavelet decomposition of both the base (reference) and input (sensed) image, the algorithm extracts the approximate coefficients from the wavelets. The reason for decomposing the images is to accelerate the computation speed by making the original images smaller. If an image is decomposed by the 2D-DWT then four sub-images can be obtained. One low-detailed sub-image can be obtained from the low frequency component and the other three more detailed sub-images can be obtained from the high frequency components. The three detailed sub-images also have the three directional edges of shapes, where a directional edge has a specified direction and orientation. In the 2D-DWT, the three detailed sub-images have vertical, horizontal and diagonal edges, respectively. The 2D-DWT can therefore detect various image features from various frequency components. However; there is a problem in that the 2D-DWT is not shift-invariant. This problem means the analysis using the 2D-DWT is sensitive to changes in phase.

WAVELET PACKETS BASED FEATURE EXTRACTION

The weakness of wavelet transform is overcome by new transform method, which is based on the wavelet transform and known as wavelet packets. Wavelet packets are better able to represent the high frequency information [6]. Wavelet transform, extract features only in low frequency bands, but the features are also present in high frequency bands. To achieve a better feature extraction use wavelet packets. Wavelet packets represent a simplification of Multiresolution decomposition [7]. In the wavelet packet decomposition, the iterative procedure is applied to the coarse scale approximation along with horizontal detail, vertical detail, and diagonal detail, which leads to a complete binary tree. Structure of three level decomposition of wavelet packet is shown in figure 2, and tree structure of wavelet packet decomposition up to the third level is shown in figure 3.

The orthogonal wavelet decomposition procedure splits the approximation coefficients into two parts. After splitting we obtain a vector of approximation coefficients and a vector of detail coefficients both at a coarser scale. The information lost between two successive approximations is captured in the detail coefficients. Then the new approximation coefficient vector is split again in the wavelet packet approach each detail coefficient vector also decomposed into two parts as in approximation vector splitting. Due to decomposition of only the approximation component at each level using the dyadic filter bank, in a normal wavelet analysis the results of frequency resolution in higher-level DWT decompositions are less desirable. It may cause problems while applying DWT in certain applications which the important information is located in higher frequency components. The frequency resolution of the decomposition filter may not be fine enough to extract necessary feature from the decomposed composition of the image. The necessary frequency resolution can be achieved by implementing a wavelet packet transform to decompose an image further. The wavelet packet method is a generalization of wavelet decomposition that offers a richer range of possibilities for image analysis. In wavelet analysis, an image is split into an approximation and a detail. The approximation is then split into a second-level approximation and detail, and the process is repeated. For n-level decomposition, there are n+1 possible ways to decompose or encode the image. In wavelet packet analysis, the details as well as the approximations can be split. This yields more than different ways to encode the image.

LL_1LL_2	LL_1HL_2	HL_1LL_2	HL_1HL_2
LL_1LH_2	LL_1HH_2	HL_1LH_2	HL_1HH_2
LH_1LL_2	LH_1LH_2	HH_1LL_2	HH_1HL_2
LH_1LH_2	LH_1HH_2	HH_1LH_2	HH_1HH_2

Fig.2 Structure of three level decomposition of wavelet packet

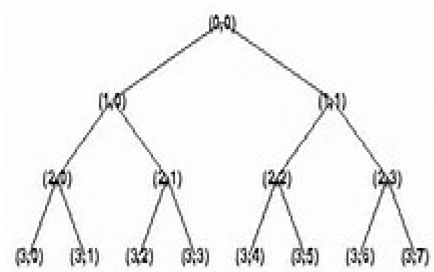

Fig.3 Tree structure of wavelet packet decomposition

The wavelet decomposition tree is a part of a complete binary tree. As stated above the wavelet packet analysis is similar to the DWT with the only difference that in addition to the decomposition of the wavelet approximation component at each level, the wavelet detail component is also decomposed to obtain its own approximation and detail components. Each component in this wavelet packet tree can be viewed as a filtered component with a bandwidth of a filter, decreasing with increasing level of decomposition and the whole tree can be viewed as a filter bank. At the top of the tree, the time resolution of the wavelet packet components is good, but at an expense of poor frequency resolution, whereas at the bottom with the use of wavelet packet analysis, the frequency resolution of the decomposed part with high frequency content can be increased.

PROPOSED METHOD

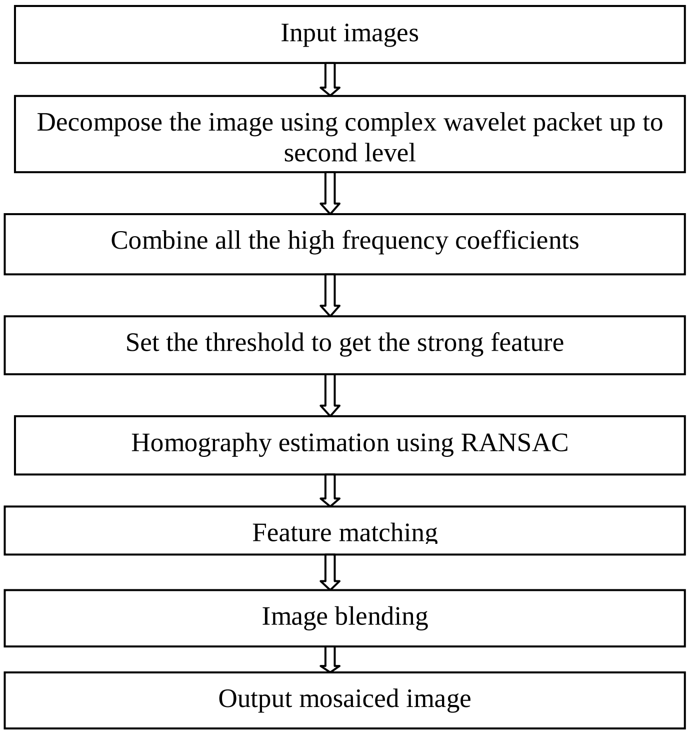

Fig.4 Block diagram for proposed method

A. Feature extraction

The figure 4 represents the Block diagram of the proposed method. In this method first decompose the image using the complex wavelet packets up to second level. At second level combine all dilated frequencies and leave the approximate coefficients, i.e. combines horizontal, vertical and diagonal frequencies. After combining all high frequencies set the threshold to get strong key points. Project these strong key points in the input image by multiplying each coefficient by four times because the input image can be analyzed in one of the fourth part of the original image. Complex Wavelet packet decomposition is similar to the ordinary wavelet packet decomposition. To get the phase information multiplies the complex term at the end of a wavelet packet decomposition tree. Figure (5) shows the combine all dilated frequency coefficients in each level of wavelet packet decomposition.

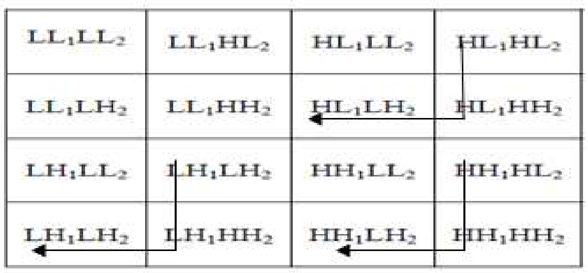

Fig.5 Combine dilated frequency coefficients

B. Feature matching

Feature matching aims to detect features and then match them. Local and global registration starts from these feature matches, locally registers the neighboring images and then globally adjusts accumulated, registration error, so that multiple images can be finely registered [11]. After points of matching have been found, they need to compare themselves. It is used a maximum correlation to determine matches between two images. It is completed by analyzing of the pixels around each point of the first image and compares them with the pixels around every other point in a second image. The most common points are taken as matching pairs. It can be seen very well from the picture, however, that many points have been wrongly correlated. This is the case of the diagonal lines that do not follow the same direction as the majority of other lines. Homography Estimation It is needed to define a model, which can translate points from one set to the other [9]. It can be used to project one of the two images on top of the other while matching most of the correlated feature points we require a Homography matrix, which has the opportunity to match the two images. First identifying the correct key points by using RANSAC. It is the algorithm to estimate the mathematical model of a set of observed data. Observed data contain both inliers and outliers. Where inliers correspond to a set of data that can be described by some set of parameters, whereas outlets cannot be described by a model. So, for an accurate model fitting, these outlets have to be eliminated.

C. Blending

Image Blending is the technique which modifies the image gray levels in the vicinity of a boundary to obtain a smooth transition between images by removing these seams and creating a blended image [8].

ALGORITHM FOR IMAGE MOSAICING USING COMPLEX WAVELET PACKETS

Step1: The first step of panoramic image mosaicing take two images of size 449X677

Step2: Decompose both original images using complex wavelet packets up to the second level only.

Step 3: Summing only the high frequency coefficients in second level decomposition, because this feature is defined as the high frequency wavelet coefficient and excluded the low frequency coefficients.

Step 4: Project these points in an image by multiplying four times of each key point location because in second level of wavelet packet decomposition the image can be analysis done on $1/4^{th}$ part of the original image.

Step 5: Plot the maxima and minima key points which are obtained from the threshold. Here total number of key points detected in both images is 871.

Step 6: After obtaining the key points in both the images next step of mosaicing process is feature matching. In this step first identifying the correct key points by using RANSAC.

Fig6. Input images of size 449X677

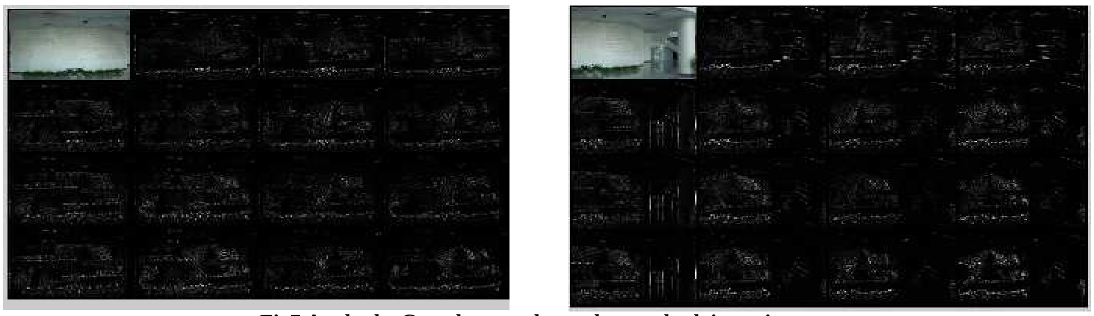

Fig7.Apply the Complex wavelet packets on both input images

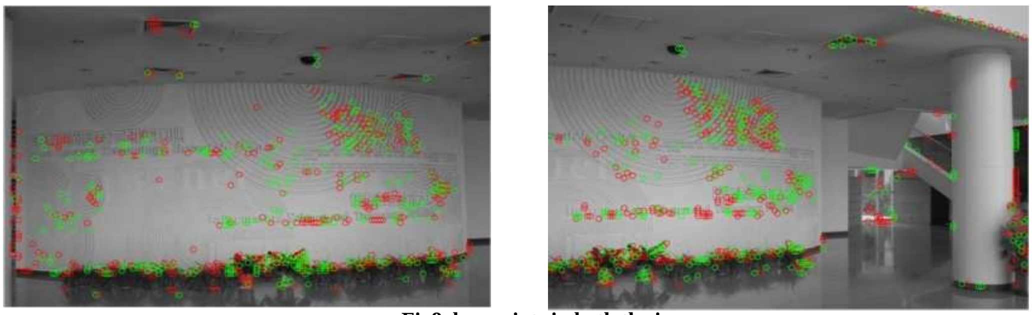

Fig8. key points in both the images

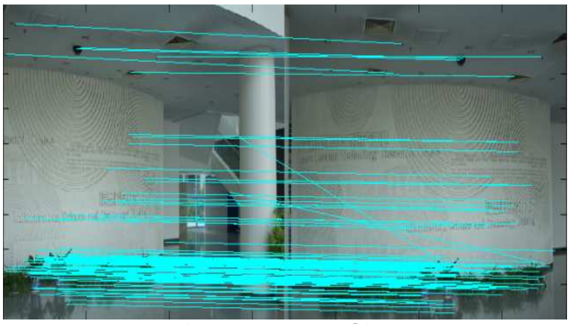

Fig9. Features matching

Fig10. Output panoramic mosaic image

Step 7: In order to recover the incorrect matches, the correct matches are filtered by identifying subsets of key points that agree on the object as well as its location, scale and orientation in the new image. Total number of key points matching is 128.

Step8: Image Blending is the technique which modifies the image gray levels in the vicinity of a boundary to obtain a smooth transition between images by removing these seams and creating a blended image.

Step9: After performing the image blending finally get the panoramic mosaiced image.

RESULTS

Fig.11 Input images

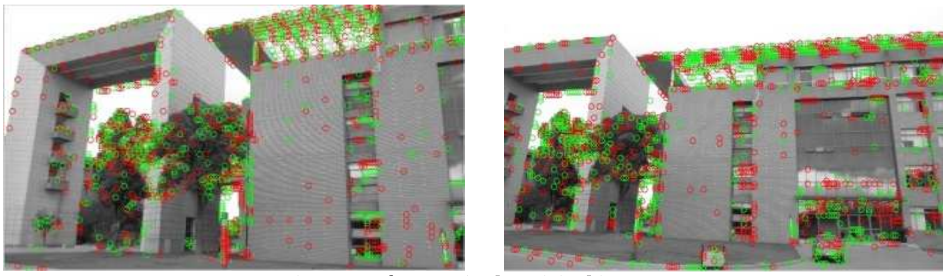

Fig.12 Key features in the original images

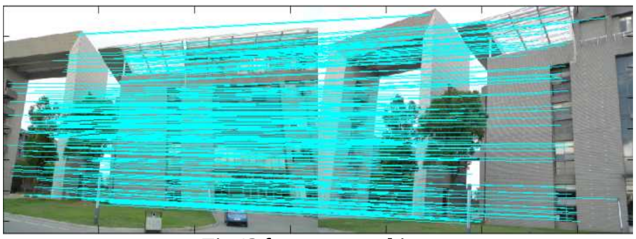

Fig 13 features matching

Fig. 14 output panorama

CONCLUSION

In this study, the problem of feature extraction is addressed and different algorithms in the literature are implemented and compared. The comparison criteria of these algorithms are computational load and time complexity. Previous methods the features are only extracted in low frequency regions only. To overcome this limitation, we propose a novel method for image feature extraction using Complex wavelet packets in this method first decompose the image using complex wavelet packets and combine only the detailed frequency coefficients in each level because the feature is a strong point it also present in horizontal, vertical and diagonal regions. An image masking is the process of combining two or more images. In image mosaicing Feature extraction is the very important role. Extracting the features this method is very simple and less time consuming when compared to the other methods.

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