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Masked Image Registration Using Wavelet Transforms

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Abstract:
Image registration is considered one of the most fundamental and crucial pre-processing tasks in digital imaging. This paper describes a fast multimodal automatic image registration algorithm that handles the alignment of IR and visible images. A multi resolution approach based on Dual Tree-complex wavelet transform is employed to speed up the process. At the coarsest level, an accurate registration estimate for higher levels is achieved, using edge detection and cross correlation. Mutual Information, on the other hand, is applied at higher levels as a matching criterion applied to the six orientation bands of the complex wavelet. The process is completely automatic, and was tested on several sets of synthetic and real data. Experimental results show that the proposed technique exhibits better accuracy than DWT-based algorithms for uni and multi-modal cases.

Index Terms:*Image Registration, Image Fusion, Multiresolution processing, Complex Wavelet Transform, Mutual Information.*

1.Introduction

Image Registration is the process of geometrically aligning two or more images acquired from different viewpoints Multi View registration), at different times (Multi-Temporal registration), by different sensors (Multi-Modal registration), or a combination of two or more of the aforementioned. In Multi View analysis, the images may differ in translation, rotation, scaling, or more complex transformations mainly due to camera positions, while in multi-temporal analysis, images of the same scene may be acquired at different times or under different lighting conditions, and finally, in multimodal analysis, images are acquired by different types of imagers or sensors. A plethora of proposed algorithms can be found for image registration which has gained, and is still receiving a lot of attention in the research community, due to its importance and necessity in many applications such as remote sensing, image mosaicing, image fusion (Surveillance, historical monument preservation), medicine (change detection, tumor growth monitoring) and computer vision (Target tracking). A detailed survey on conventional and newly proposed registration algorithms can be found in [1]. The process of image registration usually consists of four steps:

1.1.Feature Detection

It also called Control Point (CP) selection such as lines, edges, corners, etc.

1.2.Feature Matching

In which, a match between the control points chosen in step 1 is established.

1.3.Mapping Estimation

which consists of estimating the best parameters responsible of registering the sensed image to the reference one.

And finally,

1.4.Image Resampling

It consisting of transforming the sensed image using the optimal parameters found in the previous step. In manual registration, the selection of CPs is usually performed by a human operator. Despite the extensive applications of this inherently simple method, it has proven to be inaccurate, time consuming, and unfeasible due to image complexity that makes it cumbersome or even impossible for the human eye to discern the appropriate control points. In addition, it fails to meet the real time execution requirements of modern applications. Therefore, researchers have focused on automating the feature detection, to align two or more images with no need for human intervention. However, one must keep in mind that no registration algorithm will work for all kinds of applications, and at the same time, it must not be too application specific. Image registration is interpreted as the common bottleneck in the achieved accuracy of image fusion algorithms. This paper aims at developing a technique able to align infrared and visible images, which serves as a preprocessing step for an image fusion scheme published in a previous paper [2]. Thus, a fast Multi View/Multimodal automatic registration algorithm is proposed. The contribution of our work is twofold. First, employing Dual-Tree Complex Wavelet Transform (DT-CWT) as the pyramidal approach, not only offers a faster processing, but also better accuracy due to directional sensitivity and shift invariance. Second a new metric joining edge detection, cross correlation, and mutual information is proposed to handle the multimodal nature of the problem while maintaining the applicability of the algorithm to different cases.

The remainder of this paper is organized as follows: Section 2 covers the related work, followed by the developed algorithm in section 3. Section 4 summarizes the simulation results, while section 5 concludes the paper.

2.Related Work

Automatic registration has been extensively researched in the past 20 years; however, this section covers the main proposed schemes that employ multi-resolution processing, Mutual Information, or the combination of both. The idea of addressing the registration problem by applying coarse-to-fine resolution strategy has proven to be an elegant method to speed up the whole process while preserving, if not enhancing the accuracy of the algorithm. In [3], a multi-resolution scheme based on Discrete Wavelet transform (DWT) is employed to register satellite images. Maximum Modulus Maxima is applied on the LH and HL frequency bands to extract edge points, and correlation is then applied for matching. The authors in [4] developed a parallel algorithm using the maxima of DWT coefficients for the feature space, and correlation for the search space. Despite their achieved performance, the above mentioned methods operate directly on gray intensity values and hence they are not suited for handling multi-sensor images. Mutual information methods on the other hand, originating with Viola and Wells [5], are able to register multimodal images since MI represents a measure of statistical dependency between the reference and the senses images rather than gray intensity values, which vary when different types of imagers are used, or under different lighting conditions. A multimodal brain image registration is developed and presented in [6]. It combines the sum of difference (SAD) and the mutual information (MI) into a matching criterion to enhance the registration accuracy. A multi-resolution scheme is adopted making use of the LL band. Even though SAD is applied directly to the gray intensity values, the authors claim their algorithm work for multimodal images. [7] presents an automatic registration algorithm suited for airborne imagery, based on DWT and a maximization of mutual information (MMI) optimization. A similar technique is presented in [8]. The work developed in [9] on the other hand, explores a new hybrid metric based on mutual information and spatial information to register medical images.

Due to the computational burden imposed by the search over the whole image to find the best geometric transformation, multi resolution schemes were adopted and used by researchers to speed up the process. The multi-resolution pyramidal approach allows us to exhaustively search over a small image at a coarse resolution to find an estimate of transformation parameters. Once found, the search space is narrowed, and an estimate of the higher resolution parameters is found. This is repeated until the highest level is reached, thus decreasing the amount of computations required compared with the search over the whole image. Discrete Wavelet Transform (DWT) [10] has been investigated and used to speed up the registration process. However, it suffers from several shortcomings such as shift sensitivity due to the subsampling at each level, poor directionality (three orientation bands: vertical, horizontal and diagonal), and lack of phase information. The Shift-Invariant DWT (SIDWT [11]) eliminates the shift sensitivity problem at the cost of an over-complete signal representation. On the other hand, the recently proposed Dual-Tree Complex Wavelet Transform (DT-CWT [12]) not only addresses the over-completeness problem of the SIDWT, but is also characterized by a better directional sensitivity representing the image at six orientations at ±15º, ±45º, and ±75º.

3.Registration Steps

The proposed algorithm aims to register two images acquired from different sensors (Infrared and visible spectrums in our case), and from different point of views, hence the difference in rotation, translation in both directions x and y, as well as possible scaling.

The algorithm starts by decomposing the two input images, IREF(x,y) and ISRC(x,y) using the aforementioned DT-CWT(Near- Symmetric 13,19 tap filters, Q-Shift).

Let DREF,l (x,y){l=1,..,n} and DSRC,l (x,y){l=1,..,n} represent the decomposed images respectively, where l denotes the decomposition level and n is the total number of levels. Each decomposed image consists of a real part representing an approximation of the image and a complex part comprising six orientation bands (±15º, ±45º, and ±75º).

The algorithm is divided in two main parts: Registration of the lowest decomposition level n, and the registration of higher levels l =n-1, ... 1. Starting at level n, the coarsest level of decomposition, a first estimate of the transformation vector v = [tx ty] must be found. Scaling is omitted in this paper for simplicity. This step must be handled with extreme care since it constitutes the initial estimate upon which, higher levels of decomposition depend. For this reason, we choose Cross Correlation as a matching criterion due to its effectiveness and accuracy. This choice, however, suffers from two problems:

Cross Correlation cannot handle multimodal images since it operates directly on intensity values.

It is a computationally demanding task.

To overcome the situation, we propose to extract edge maps for the reference and source low passed images, □ref and □src respectively. Operating on edge maps instead of the image itself not only solves

the correlation limitation (correlating edge information instead of intensity values), but also have reduced computational requirements since the majority of the map consists of zero values except for edge locations.Here, we demonstrate the use of masked FFT registration for object tracking and image stabilization. We apply our masked FFT NCC algorithm to two distinct translation registration applications of the well-established coastguard sequence (http://media.xiph.org/video/derf/). A number of frames from the image sequence are shown in Fig., which shows two boats passing in the foreground as the camera initially pans to the left (following the small boat) and then to the right following the large boat). This image sequence has been used in numerous publications, including that of Fitch et al. [33], which we described in Section I. In that reference, the authors demonstrated the ability of their algorithm to register the background while ignoring the fast-moving boats in the foreground.

For example, in Fig.6 of their paper, they generate a mosaic Fig.8, Selected images from the 300-frame coastguard sequence. The camera initially pans to the left while following the small boat. When it sees the large boat, it suddenly pans up between frames 65 and 75 and then starts to pan right to follow the large boat. Beyond frame 272, there is no longer any overlap with the first frame; hence, we only consider up to this frame.

Fig.9, Stabilizing the background by defining a mask for only the first frame.

The mask is defined to be invalid in the water region. The mosaic is computed as the mean of all images transformed to the initial image, and this averaging causes the boats to disappear. The plot on the right shows the (blue) - and (red) -components of the transformation over time. The abscissa gives the frame number, and the ordinate gives the accumulated translation. The translations are initially negative as the camera pans to the left following the small boat and then become positive as the camera starts to pan right following the large boat.

The translations change very little, except between frames 65 and 75 when the camera suddenly pans up.

that accurately aligns the background region, and Fig.7 of their paper presents the transform calculated between frames 1 and 80 of the sequence.

Our algorithm enables control over the definition of the mask, and we will demonstrate how different masks can yield very different useful results. We first aim to stabilize the background while the boats move and pass each other in the foreground.

A mask can be defined for either the fixed image, the moving image, or both. For a tracking application, we may not be able to define a mask for every frame because we may not know where the ROIs will be in the following frames. Instead, we can simply define a mask only for the initial frame in the sequence. In our

case, we define a mask for the initial frame (fixed image) that is set to 1 in the background and set to 0 in the water region of the image. Since there is a dark vertical line on the right of every image (an artifact), our mask is also set to 0 in that region. The masks for the rest of the frames are set to all ones (no masking).

After defining the mask for the initial frame, we register the first image along with its mask to all of the rest of the images using masked FFT registration. The result is shown in Fig. 9, where we have generated a mosaic of the mean of all of the transformed images. In this figure, the background is well registered and the foreground looks like a blur with the boats almost completely averaged away. We also calculated the transform between frames 1 and 80 and found it to be same values as those calculated by Fitch et al. in [33]. Note that we could have instead registered the images frame by frame to attempt more accurate registration since adjacent images have greater overlap. However, this would require the definition of masks at each step since the fixed image would be continually changing.

3.1.Algorithm 1

Multi-resolution Registration

START

DREF, l← DT-CWT (IREF, n) , DSRC, l ←DT-CWT(ISRC, n)

IF l=nDO

Mref←EdgeMap(R{DREF,n}),MSRC←EdgeMap(R{DSRC,n})

Vinit←arg max

v

END IF

WHILE l>=1DO

Adjust such interval according to Vl-1

V1←arg max [I(R{DREF,1},T(R{DSRC,1}))]

v [+I(||C{DREF,1}||,T(||C{DSRC,1}||))]

END WHILE

Warp image using V=[α1 2*tx-12*ty-1]

END

To further reduce the computational requirements, an alternative search method, consisting of splitting the search space into complementary sub-spaces is proposed in [4] and can be easily applied to our proposed method to further reduce the computational burden. It is however omitted due to lack of space.

4.Experiments And Result

The proposed algorithm was developed and tested on several sets of uni-modal and multi-modal images. However, we limit the simulation results to two sets only due to the lack of space. For each set of images, three algorithms were implemented: (1) A Discrete Wavelet Transform employing correlation at the lowest.

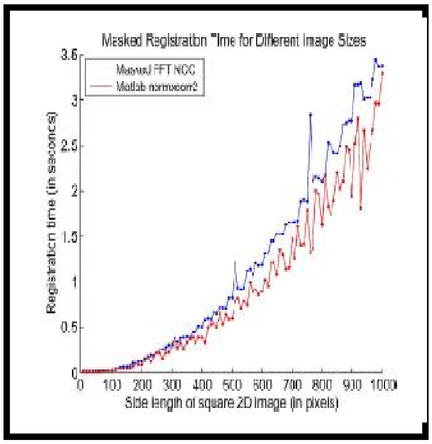

Figure 1: experiment

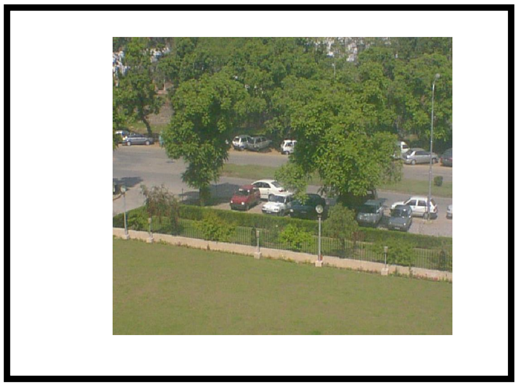

Figure 2:

Figure 3

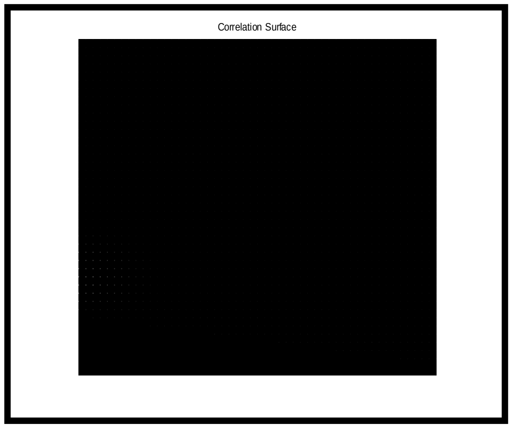

Figure 4

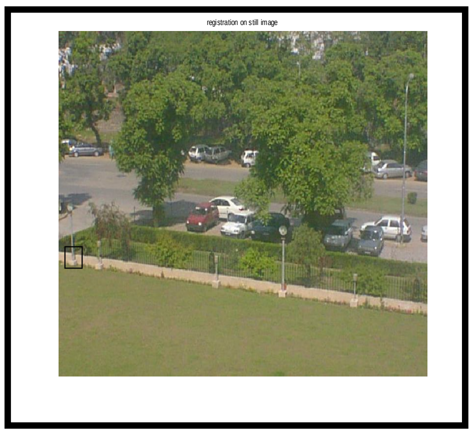

Figure 5

5.Conclusion

In this paper, a new technique for multimodal automatic image registration algorithm is presented. To speed up the processing, the algorithm is employed in a pyramidal fashion based on Dual tree complex wavelet transform. At the lowest level, edge maps are extracted and the matching is based on cross correlation measure. The search interval is then refined for higher levels employing Mutual Information as a matching criterion due to its ability to register multimodal images and its light computational load. The developed technique handles multi-modal as well as uni-modal cases and has shown to have superior accuracy when compared to its DWT counterpart.

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