IMAGE REGISTRATION FOR SUPER RESOLUTION USING SCALE INVARIANT FEATURE TRANSFORM, BELIEF PROPAGATION AND RANDOM SAMPLING CONSENSUS

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ABSTRACT

Accurate image registration is crucial for the effectiveness of super resolution. In super resolution, image registration is used to find the disparity between low resolution images. In this paper an image registration approach based on a combination of Scale Invariant Feature Transform (SIFT), Belief Propagation (BP) and Random Sampling Consensus (RANSAC) is proposed for super resolution. The SIFT algorithm is used to detect and extract the local features in images, BP is used to match the features while RANSAC is adopted to filter out the mismatched points and then estimate the transformation matrix. The proposed method is compared with traditional SIFT to verify its accuracy and stability. Finally, the result of using the proposed approach in the super resolution application is given.

1. INTRODUCTION

Super resolution is a method to reconstruct a high resolution image from a sequence of low resolution images. High resolution images are desirable in many applications such as clinical diagnosis, high quality video conferencing, high definition television broadcasting, blu-ray movies etc. There are three major steps in super resolution i.e., image registration, interpolation and restoration. Accurate image registration is an important factor in super resolution performance. The demand for accuracy in image registration is increasing because of the super resolution applicability in various fields.

There is a great deal of the image registration research in the literature. Reported methods can be classified into two main approaches: intensity-based methods and feature-based methods. Intensity-based methods compare the intensity patterns in images via correlation metrics, while feature-based methods find correspondence between image features. Scale Invariant Feature Transform (SIFT) is one of the most popular feature-based methods introduced by Lowe [1]. SIFT is able to detect and describe local features that are invariant to scaling and rotation. Various improvements have been made to the SIFT algorithm, and a recent one reported in [2] uses belief propagation (BP) to achieve better matching than with the minimum Euclidean distance method [1] which completely ignores the geometric information among the descriptors. In [3] Random Sampling Consensus (RANSAC) [4] is used to improve the mismatch points in the SIFT algorithm and then a support vector machine is adopted to estimate the transformation matrix. In [5] the algorithm is improved by applying effective mismatch filtering using the genetic algorithm. In [6], matching in the traditional SIFT algorithm is improved by using principal-component analysis (PCA) and RANSAC is used to estimate the homography matrix. In [7] the SIFT algorithm is used to register medical microscopic image sequences where the Gaussian weighting function is used to optimise the feature descriptor.

In this paper we demonstrate effectiveness of the SIFT with BP algorithm [2] for image registration in super resolution imaging, and further improve the result by applying RANSAC for eliminating the remaining mismatched points and estimating the transformation matrix. The rest of the paper is organized as follows. A brief review of the background is presented in the next section. In Section 3, we describe the implementation of the proposed method. Experimental results are given in Section 4. We conclude and address future work in Section 5.

2. IMAGE REGISTRATION FOR SUPER RESOLUTION

Generally, three problems need to be solved when performing super resolution: (i) image registration, (ii) interpolation and (iii) restoration. In this paper, we focus on the image registration step, which is a crucial step in super resolution.

Image registration is used in super resolution to register low resolution image frames. A subpixel-registered image sequence of the same scene potentially contains more information than any single view alone. Image registration enables finding subpixel shifts and hence extracting useful information from multiple frames. Many methods are proposed for this task (see [7] for a survey). The SIFT algorithm is one the most popular feature-based image registration methods often used in panoramic imaging, medical imaging, robotics, and surveillance.

After image registration, the relative pixels positions of all low-resolution images in the sequence in reference to the first image are identified. Then we can project this information on high-resolution grid. For this task we use the algorithm of [9], though any other method can also be applied.

The following sub-section discusses the background of image registration techniques used in this paper.

2.1 SIFT feature extraction

The SIFT algorithm [1] presents a method for extracting local features that are tolerant to scale and illuminations changes as well as rotation. There are four main steps in extracting the local features: (i) keypoints detection, (ii) keypoints localization, (iii) orientation assignment, and (iv) keypoints descriptor generation.

First, a set of Difference of Gaussian images covering the range of scales are generated using a Gaussian pyramid and then local minima and maxima are tracked through scale space by comparing each pixel with its 36 nearest neighbors. Each local minima and maxima form a candidate keypoint.

The second step is to determine location and scale for each candidate keypoint. The points with low contrast and poorly localized edge points are rejected.

In the orientation assignment step, each keypoint is assigned a direction based on the local image gradient. Additional keypoints will be created if strong directions exist.

Lastly, the local neighborhood of each keypoint is used to generate an array of SIFTdescriptors. The SIFT descriptor is generated by calculating orientations and magnitude of the pixel neighborhood relative to the keypoint in question. Each descriptor is made by an area of 3 x 3 pixels and consists of 8 bins. Each pixel contributes with its magnitude to the bin closest to its orientation. More details on how SIFT descriptors are calculated can be found in [1].

2.2 Descriptor matching using belief propagation

For image matching, descriptor vectors of all keypoints are stored in a database. In traditional SIFT [1], matches between keypoints are found based on Euclidean distance.

In [2], belief propagation (BP) is used in the matching process where the keypoint matching is formulated as a global optimisation problem. Detailed steps on how BP is used in the SIFT matching process can be found in [2].

2.3 RANSAC and transformation matrix estimation

RANSAC is a robust estimator originally proposed by Fischler and Bolles in 1981[4] where it was used to derive a usable model from a set of data. In [3], RANSAC is used to filter out the incorrectly mapped points that come from the imprecision of the SIFT model.

The correct matching features are classified into inliers and outliers using RANSAC. Inliers are the data that adhere to the model while the outliers are the data that do not. The RANSAC algorithm starts by randomly selecting sets of corresponding points. For each possible set of four keypoints at the reference image and their respective matches at the target image the mapping transform is found. Then transformation matrix is estimated using those points as follows:

$$\begin{pmatrix} x' \\ y' \\ z' \end{pmatrix} = A \begin{pmatrix} x \\ y \\ 1 \end{pmatrix}$$

where $(x', y') \longleftrightarrow (x, y)$ are pixel point correspondences, and A is a 3x3 transformation matrix.

Using the transformation matrix, the symmetric transfer error $d(x, A^{-1}x')^2 + d(x', Ax)^2$ is calculated for every matching point, and the inliers that are less than the threshold value are counted. Here $d(x, y)$ is the Euclidean distance between points x and y. Then the same procedure is applied to the rest of the keypoints in the reference image, and spatial coordinates of transformed keypoints are compared to the coordinates of the respective keypoints in the target image. This allows establishing the number of keypoint pairs that fit the model within a certain tolerance. The model that supports maximum number of keypoint pairs (consensus set) within a transform model is considered as optimal. Then the model will transform the target image to the reference image, so that corresponding points in both images are spatially close to each other.

3. THE PROPOSED METHOD

The proposed image registration method for super resolution is shown in Figure 1. We assume that Test image needs to be registered with Reference image. First, the original SIFT algorithm [1] is used to extract the local features in both images. The extracted features are then matched using the BP algorithm as in [2]. Next, mismatched points that remain after the BP matching are eliminated using RANSAC. Finally, the transformation matrix is estimated once all the correct matching points are established, and the image is resampled using the optimal transform model.

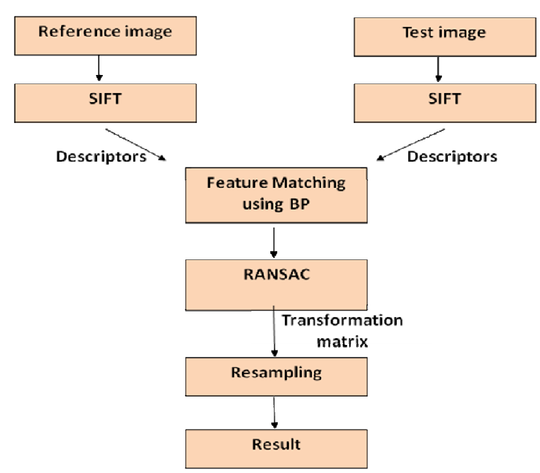

Figure 1: The block diagram of the proposed method.

One example of the keypoints matching obtained by SIFT, SIFT-RANSAC and SIFT-BP is shown in Figure 2 (a)-(c). Keypoints are shown by blue circles and matches with red lines. One can see that SIFT-RANSAC (without BP) eliminated two wrong matches after SIFT, and SIFT-BP eliminated 4 wrong matches.

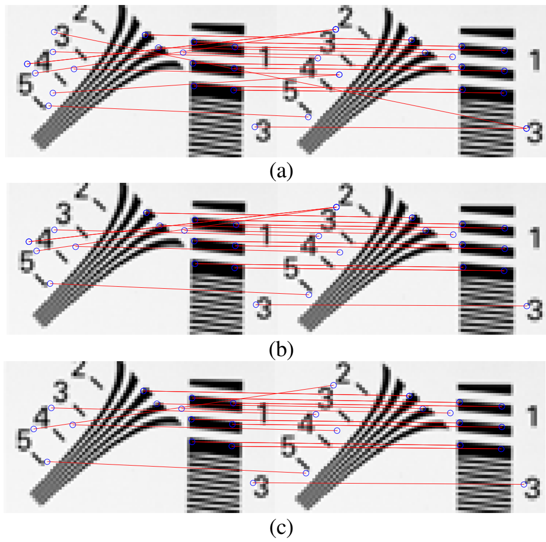

Figure 2: Keypoints matching of the original low resolution images (a) using original SIFT (25 matches) (b) using SIFT-RANSAC (23 matches) (c) using SIFT-BP (21 matches).

Figure 3 demonstrates that the proposed approach eliminates two remaining wrong matches by applying RANSAC after the BP algorithm. Thus, using RANSAC after BP can reduce the number of wrongly matched keypoints that can potentially improve the image registration result, and consequently super resolution performance.

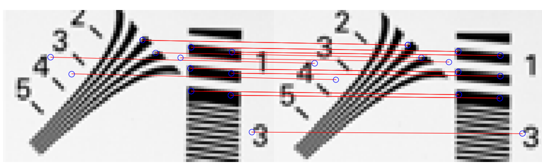

Figure 3: Keypoints matching using the proposed method (19 matches).

4. RESULTS

This section presents experimental results and compares super resolution performance when using SIFT, SIFT-RANSAC, SIFT-BP, and SIFT-BP-RANSAC for image registration. The performance was tested on simulated and real-world low resolution images. We present results of image registration only, and super resolution.

The first experiment was based on two simulated images used in Section 3. The test image was shifted by random translations in pixels, and the original image was used as a reference. Figure 4 compares image registration results obtained with SIFT, SIFT-BP [2], and SIFT-RANSAC [3]. SIFT-BP and the proposed SIFT-BP-RANSAC method gave the best results. It can be seen from Figures 4 (c) and (d) that the registered image based on SIFT-BP has artefacts due to wrong registration at the first rectangular close to number 1 on the right of the image. This problem was removed by eliminating two more bad matches with RANSAC.

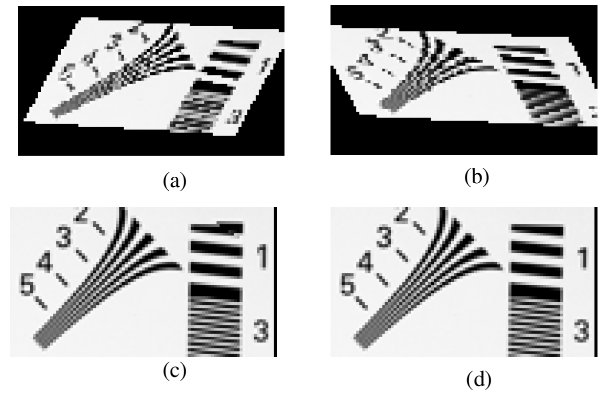

Figure 4: The registered image using (a) SIFT (b) SIFT- RANSAC (c) SIFT-BP (d) the proposed method.

After image registration, we proceed with super resolution. In this work we use the algorithm of [9] for robust super resolution, i.e., to perform interpolation and restoration of the registered image. Note however, that most other super resolution methods can be used instead of [9].

Figure 5 shows the resulting super resolution images obtained when SIFT, SIFT-BP, SIFT-RANSAC, and SIFT-BP-RANSAC were used for image registration. The improved quality of images after super resolution with SIFT-BP and SIFT-BP-RANSAC image registration compared to the original low-resolution image shown in Figure 6 (left) is obvious. SIFT-BP still suffers from the same artifacts as after registration.

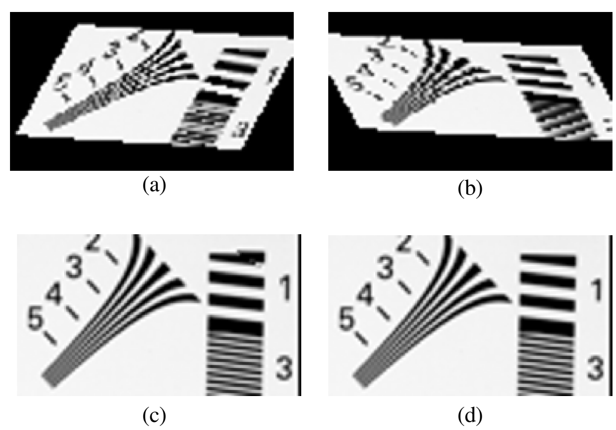

Figure 5: Results of super resolution for (a) SIFT (b) SIFT-RANSAC (c) SIFT-BP (d) the proposed method.

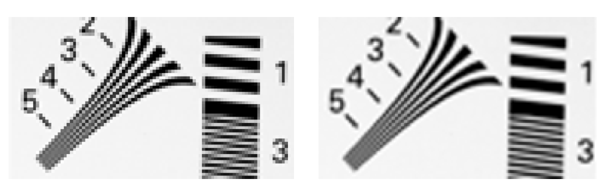

Figure 6: (left) One of the low resolution image (52x93) (right) High resolution image (208x372).

(a) (b) (c) (d)

Figure 7: Keypoints matching using (a) SIFT (96 matches) (b) SIFT-RANSAC (83 matches) (c) SIFT-BP (48 matches) and (d) the proposed method (48 matches).

Figure 5 also shows the importance of the image registration step, since super resolution on wrongly registered images with SIFT and SIFT-RANSAC (shown in Figures 5 (a) and (b), respectively) led to very poor high resolution results in Figures 5 (a) and (b), respectively.

The second experiment is given to show the effectiveness of the proposed method with real-world images. Figure 7 shows the keypoints matches obtained by SIFT, SIFT-BP, SIFT-RANSAC, and SIFT-BP-RANSAC. We observe mismatch points in the original SIFT and SIFT-RANSAC but most of the mismatched points were removed after BP.

After the wrong matches have been removed the inliers are used to solve the transformation matrix. Figure 8 shows the registration results. The red circles in Figure 8 highlight the most obvious errors in the registered images after resampling. For example, in Figure 8(a) and 8(c) the text has been distorted and the same can be said for the arrow in Figure 8(b). In Figure 8(d) however, the proposed method offers improved performance as no such artefacts can be seen in the registered image.

As demonstrated, applying RANSAC after BP improves image registration performance. As a direct result of the registration improvement, the performance of the super resolution algorithm is significantly improved. This is illustrated in Figure 9 and 10 from which we can see better super resolution performance as a result of more accurate registration. The red circles again highlight the most obvious artefacts in the resulting images. The super-resolution image obtained using SIFT-BP-RANSAC for image registration has obviously the highest visual quality.

In addition to the above test images, we further tested the proposed methods using images from the Oxford buildings dataset [10]. The results obtained for these test images are similar to those reported.

5. CONCLUSION

In this paper, we propose using SIFT-BP-RANSAC based image registration for image super resolution. The technique was applied on simulated and real-world images and the initial results are encouraging especially when compared to the traditional SIFT method. The advantage of the proposed method lies in its ability to overcome the outliers introduced in the SIFT-BP method and hence correctly estimate the transformation matrix. The resulting super-resolution images show better visual quality compared to the case when SIFT SIFT-BP or SIFT-RANSAC alone are used for image registration.

(a) (b) (c) (d)

Figure 8: Registered image using (a) SIFT (b) SIFT-RANSAC (c) SIFT- BP (d) the proposed method

(a) (b) (c) (d)

Figure 9: Super resolution results with (a) SIFT (b) SIFT-RANSAC (c) SIFT-BP (d) the proposed method

Figure 10: (left) One of the low resolution image (128x128) (right) High resolution image (512x512)

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