A New Point Matching Method for Image Registration

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Abstract: - This paper presents a new point matching algorithm which uses color pixel information in order to accomplish the registration task. Parameter estimation is carried out with a similarity transform estimated for sets of two pairs of points. The problem investigated in this paper is finding an optimal threshold that can reject possible mismatches between pairs of points, in order to simultaneously increase the estimation accuracy and reduce the processing time. The solution is analyzed and performances are evaluated.

Key-Words: - image registration, robust estimation, mean shift, similarity transform, point matching, optimal threshold

1 Introduction

Feature-based methods in image registration frequently encounter the correspondence problem. Points (region corners, line intersections, points on curves with high curvature) are among the most frequently used features. They are expected to be stable in time to stay at fixed positions during the whole experiment. Starting from these data sets, the registration algorithm is overlaying two or more images, of the same scene taken at different times, from different viewpoints, and/or by different sensors, under an optimal transformation that has to be found. This problem is an interest in many domains, like remote sensing, computer vision and medical imaging [1]. The solution presented in this paper is devised to be applied to a video sensor network which is composed of distributed camera devices capable of processing and fusing images of a scene from a variety of viewpoints into some form, more useful than the individual images.

The correspondence between the features can be classified in two categories: feature-based and region-based methods. Due to the fact that the region based registration is prone to errors generated by segmentation and different color sensitivities of the cameras, image point features can be used instead. This approach has been shown to be more robust with view point, scale and illumination changes, and occlusion. However, the presence of errors is a problem as well, especially in the automatic feature extraction case.

The existences of outliers assume that many point features may exist in one point-set that have no corresponding points (homologies) in the other and hence need to be rejected during the matching process.

A point future registration algorithm needs to address these issues. It should be able to solve for the correspondences between two point-sets, reject outliers and determine a good non-rigid transformation that can map one point-set onto the other. In the domain of image registration, many authors have tried and succeed to resolve the problem of point extraction and matching, and also the problem of outliers. For example, in [2] Papadepetris et al. presented a robust point matching framework to improve its ability to handle larger point sets with greater computational efficiency. The method gave good results, with a successful application on large real 3D data-sets. In [3] Chui has developed point matching algorithm for non-rigid registration which is good for non-rigid registration. The algorithm utilizes the softassign, deterministic annealing, the thin-plate spline for the spatial mapping and outlier rejection to solve for both the correspondence and mapping parameters. In [4] two algorithms are proposed for resolving the point pattern matching problems. One algorithm is using branch and bound search, simple but relatively slow. The second algorithm is called bounded alignment, based on combining branch and bound with computing point alignments to accelerate the search. The algorithm seems to be faster, but being a Monte Carlo algorithm, may fail with some small probability.

Another approach recently proposed in Belongie et al. [5] adopts a different strategy. For each point chosen, lines are drawn to connect it to all other points. The length as well as the orientation of each line is calculated. The distribution of the length and the orientation for all lines (they are all connected to the first point) are estimated through histogramming. This distribution is used as the shape context for the first point. Basically, the shape context captures the distribution of the relative positions between the currently chosen point and all other points. However, it is unclear how well this algorithm works in a registration context.

In [6] the point matching problem for object pose estimation has been turned into a classification problem. Each point in the "training" image is a class. In general, the method usually gives a little fewer matches, and has a little higher outlier rate than SIFT [7], but it is good enough for RANSAC to do the job.

In this paper, we report results of the evaluation of our new point matching algorithm [8], and address the problem of finding an optimal threshold for the proposed method. The rest of the paper is organized as follows: the next section describes the point matching method used in this work, with the new median point matching method. Section III analyzes the results of this method under different thresholds, in order to determine the optimal threshold. Section IV presents evaluation results on real images. Finally, conclusions of this work are presented in Section V.

2 Median point matching for image registration

Our image registration approach models the change between two images by the similarity transform equations:

$$\begin{bmatrix} q_x \\ q_y \end{bmatrix} = \begin{bmatrix} s & 1 \\ 1 & s \end{bmatrix} \begin{bmatrix} \cos(\varphi) & -\sin(\varphi) \\ \sin(\varphi) & \cos(\varphi) \end{bmatrix} \begin{bmatrix} p_x \\ p_y \end{bmatrix} + \begin{bmatrix} t_x \\ t_y \end{bmatrix}, \qquad (1)$$

relating the old pixel coordinates (p_x, p_y) to the new ones, (q_x, q_y). The four parameters of the transformation can be determined from the correspondence of two pairs of points. A parameter vector $p = [s,\ \varphi,\ tx,\ ty]^T$ is generated from equation (1), using two pairs of points.

Suppose the pairs of points are $(p_x^1, p_y^1) - (q_x^1, q_y^1)$ and $(p_x^2, p_y^2) - (q_x^2, q_y^2)$. The components of the parameter vector are acquired by solving the system of equations obtained after using $(p_x^1, p_y^1), (q_x^1, q_y^1), (p_x^2, p_y^2), (q_x^2, q_y^2)$ in equation (1) and solving the system of four equations.

Since the real point correspondences are unknown, in the spirit of the RANSAC algorithm, we have to generate several solutions and to test them for consistency with the others. To this end, a meanshift robust estimator is used to find a maximum likelihood estimate from the partial solutions. Regarding parameter estimation and the uncertainty of the feature matching process, robust methods have to be used to find the geometrical transform optimally mapping the sets of points detected in a pair of images.

In order to reduce the computational burden and eliminate some of the false point correspondences, giving outlier solutions, we use the median point matching method. The median point matching method is based on measuring some information extracted from pixels located at mid distance between pairs of points (figure 1) and to compare them in order to eliminate incompatible matches. Altogether, such points are located in more homogeneous regions and therefore are less affected by the exact positions of the feature points. The median of a line segment is invariant to translation, rotation and rescaling and therefore so is the colour information in the median points.

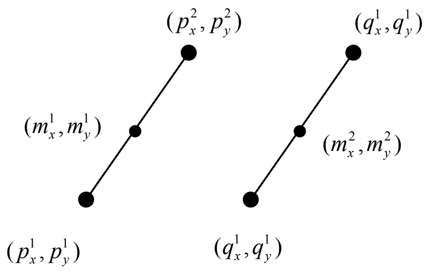


Fig.1 Feature points and median point representation

The median point matching method calculates the median point $m_i^j, i = 1,2, j = 1,2$ between the pairs of points p_i and q_i (figure 1).

The simplest type of similarity measures only regards pairs colors at the same pixel positions in the two images. To compute the norm is needed to find the color of these points:

$$D(\mathbf{m_1}, \mathbf{m_2}) = \left\| \mathbf{c}(\mathbf{m_1}) - \mathbf{c}(\mathbf{m_2}) \right\|^2, \qquad (2)$$

where c($\mathbf{p}_i$) are the color vectors of points $\mathbf{p}_i$. A match is considered valid if

$$D(\mathbf{m_1}, \mathbf{m_2}) < T, \qquad (3)$$

where T is a suitable threshold. If the norm of the color difference is larger that the threshold then the corresponding matching pair is considered mismatched and is eliminated.

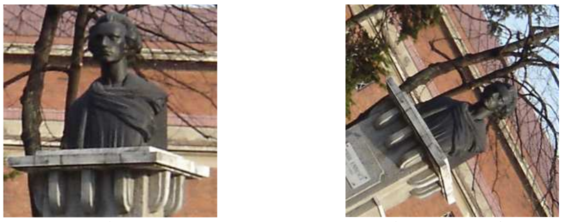
3 Finding the optimal threshold

The point mapping technique is a primary approach taken to register two images that type of misalignment is unknown. The general method consists of three steps. In the first step features in the images are computed. The second step is identifying feature correspondences in pairs of images. And the last step is estimating parameters of geometrical transforms optimally mapping features between pairs of images.

The level of the threshold highly influences the elimination of points. If the threshold is too high, many outliers could be chosen like good, allowing many false matches. This results in increased processing time and increased percentage of outliers, which in turn affects the registration accuracy. Conversely, a low threshold results in missing valid correspondences. When the number of available points is low, such an event is undesirable. Therefore, choosing an optimal level of the threshold has to be addressed.

The best threshold varies for images with image content. To test the best strategy for threshold selection, we made experiments with several types of images, as illustrated in figure 2. The images have different features. They differ by the objects with in, scale and angle. They contain a common field of view, obtained for different camera positions and orientations. All sets of points contained outliers and no correspondence information was used in the estimation. The 1D mean shift estimator was used for both methods, with *Epanechnikov* kernels [9]. Estimation scale was set equal with the inter-quartile distance of the data.

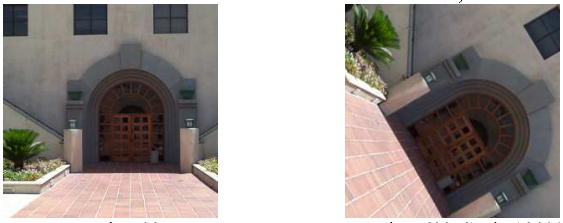
To find the optimal threshold, we carried out eleven experiments. Each experiment was realized for six images (figure 2). Constant values - 2, 5, 10, 15, 20, 25, 35, 50, 70, 90 and 100 - for the threshold T were used in the experiments.



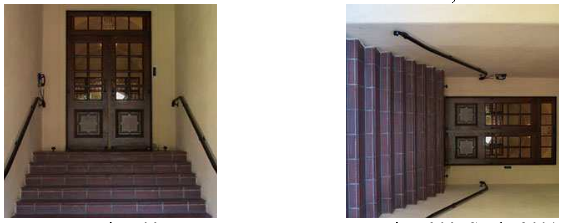
Rotation 0° Rotation 60°, Scale 70%

Rotation 0° Rotation 45°, Scale 80%

Rotation 0° Rotation 45°, Scale 0%



Rotation 0° Rotation 60°, Scale 120%



Rotation 0° Rotation 90°, Scale 80%

Rotation 0° Rotation 45°, Scale 80%

Fig.2 Images used in the registration algorithm

Graphical results of the tests for all parameter solution vector components are given in Fig. 3-7. Figure 3 contains the results of the angle estimation error. It can be observed that a too low threshold leads to a high estimation error while the lowest estimation error is obtained for a relatively low threshold. On the other hand, if the threshold is too high, the number of mismatched points is higher and the registration process is far away from a good one. In figures 4, 5 and 6 the best estimation error for the parameters of the geometrical transformation is obtained also for a low value of the threshold, in our case 5, a higher value leading to a poor quality registration. In synthesis, the threshold level 5 lead to the lowest average error over the set of experiments.

In figure 7 the average number of solutions accepted by every threshold is presented. This number was compared with the correct matches for each experiment. Again, the threshold level 5 lead to the best agreement between found matches and true correspondences.

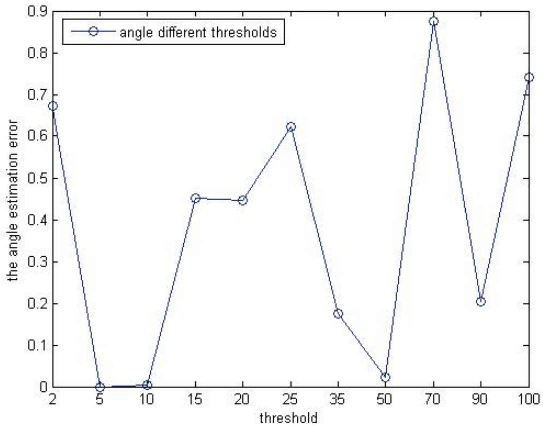


Fig.3 The angle factor error.

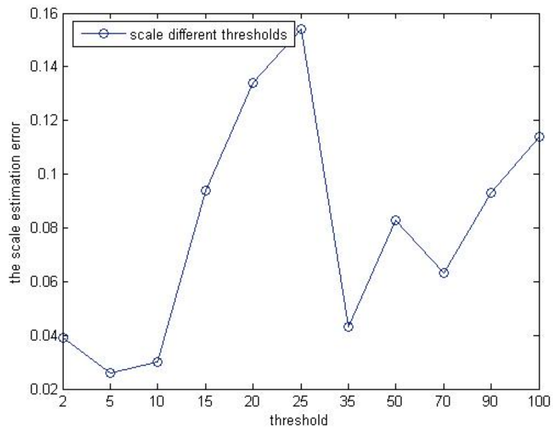


Fig.4 The scaling factor error.

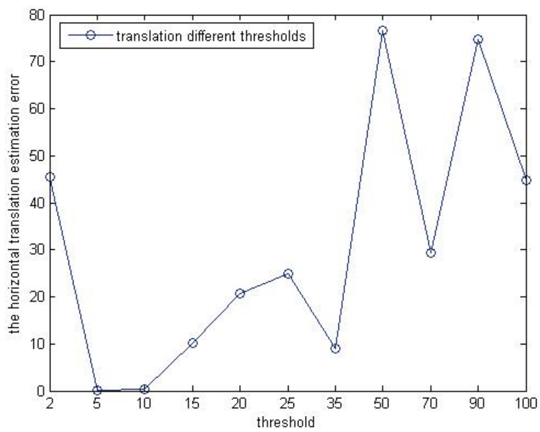


Fig.5 Horizontal translation error.

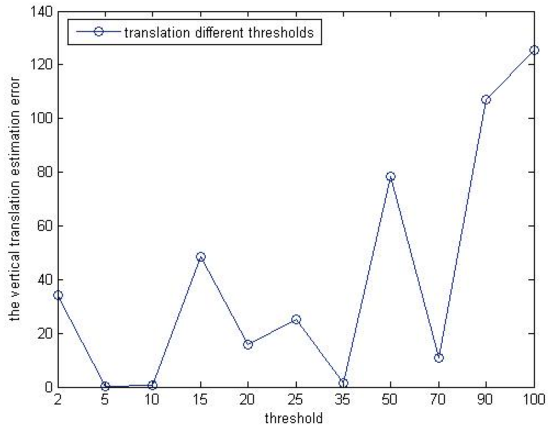


Fig.6 Vertical translation error.

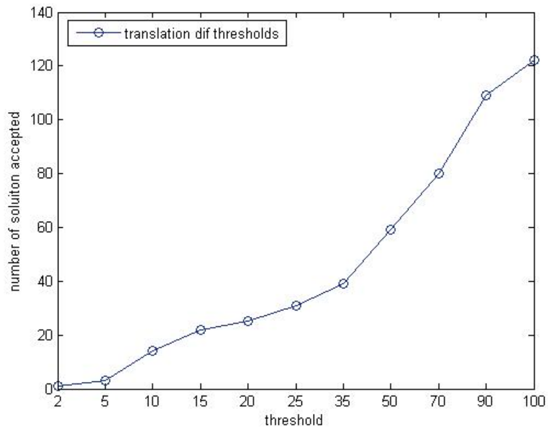


Fig.7 The number of solutions accepted.

4 Conclusion

This paper investigates the usefulness of a new point matching method, called median point matching, in image registration. Taking advantage of the smoothness property of median points, the proposed method is less sensitive to noise.

The optimal threshold found in our experiments is the one which allows passing an approximate number of solutions close to the number of real correspondences. By finding an image-adapted optimal threshold in feature matching, the combinational number of point matches became small; also the number of possible mismatches and computational time became smaller. The low threshold value found by experiments suggests that a higher rejection rate is better than a lower one than the optimal one. The algorithm could be modified when the number of available points is low. In such a case, the threshold could be increased until a proper number of matching points is found.

The proposed method has a low computational cost and is seen like an additional test which complements the traditional registration methods.

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