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A New Point Matching Method for Image Registration Using Pixel Color Information

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***Abstract* –The solution investigated in this paper is based on a mean shift estimator for feature point matching. We propose a new method based on pixel color information, to reject possible mismatches between the pairs of points, in order to simultaneously increase the estimation accuracy and reduce the processing time. The method is part of an image processing tool developed for video sensor localization in Wireless Sensor Networks. The solution is analyzed and tested for performance evaluation.**

Keywords: mean shift estimator, image registration, video sensor localization

I. INTRODUCTION

To accomplish a registration task, two or more images, of the same scene taken at different times, from different viewpoints, and/or by different sensors, are given with the purpose of overlaying them 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 [2]. Our interest in the problem stems for a wireless sensor network (WSN). In this paper a registration technique is 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.

There are two tasks which are needed to be handled during the registration process: feature selection and feature matching. Feature selection can be carried out manually or automatically (with a corner detector). In feature matching there are two problems: the correspondence and the transformation. While solving either without information regarding the other is quite difficult, an interesting fact is that solving for one once, the other is known is much simpler than solving the original, coupled problem.

The correspondence between the features can be classified in two categories: future-based and region-based methods. The region based registration is prone to errors generated by segmentation and different color sensitivities of the cameras. To avoid the difficulties mentioned, 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.

One common factor that gives birth to errors is the noise arising from the processes of image acquisition and feature extraction. The presence of noise means that the resulting feature points cannot be exactly matched. Another factor is the existence of outliers, 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 all 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, Hsieh et al. [3] proposed a method of feature extraction called feature point extraction using wavelet transforms. By defining a similarity measure metric called crosscorrelation, sets of correct matching pairs between the images were find and the correspondences between the features was established. Their method was an improvement in the sense of efficiency and as well as reliability for the image registration problem.

In [4] Chui has developed point matching algorithm for non-rigid registration which is good for on-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. It is based on the notion of one-to-one correspondence, but it is possible to be extend it to the case of many-to-many matching [5], which is the case of dense feature-based registration.

In [6] two algorithms are proposed for resolving the point pattern matching problems. One algorithm is

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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. [7] adopts a different strategy. A new shape descriptor, called the "shape context", is defined for correspondence recovery and shape-based object recognition. 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 [8] 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 [9], but it is good enough for RANSAC to do the job.

The approach in this paper regarding the registration algorithm follows the previous work [1] on registration, in the case of wireless video sensor network. An improvement of feature detection and matching is accomplished with the help of the pixel color. The rest of the paper is organized as follows: the next section describes the previous work, a localization technique using the registration process in the case of Wireless Sensor Networks. Section III analyzes the point matching based on pixel color information. Section IV presents evaluation results on real images. Finally, conclusions of this work are presented in Section V.

II. PREVIOUS WORK

In the previous work [1], a localization technique using the registration process was proposed only in the case of Wireless Sensor Networks based on video sensors. It uses a set of images gathered from all sensor nodes in an after deployment setup-phase and tries to discover matching areas in these images. The features were represented by image points, detected in both images. Ideally, they are spread over the entire image and stable in time during the registration process.

The feature matching process was combined with the parameter estimation of the geometrical transform. Two similarity transforms were implemented here, the separate and simultaneous.

The approach starts from the system of equations:

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

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. A meanshift robust estimator is used to find the best estimates from the partial solutions and a final step uses this information to compute video-field overlap between cameras on network sensors.

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. A meanshift estimator is used in our work, because it copes well with the outliers in the data set. The results were good, when the overlap between images was high and the feature points stable.

III. POINT MATCHING BASED ON PIXEL COLOR

Previous methods are based on measuring some information extracted from a neighborhood of feature points and to compare them in order to eliminate incompatible matches. The simplest information may be the pixel intensity or color. However, since typical feature points, like corners [], are located in regions with fast changes, slight positioning errors may result in high variation in the neighborhood information. Moreover, scale differences make the problem most severe. The basic idea of our approach is to compare image information extracted from pixels located at mid distance between pairs of points. Most often than not, 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 theoretically the color information in the median points is also invariant to the mentioned transforms. Color information is also very cheap to extract, keeping processing costs to a minimum level. In fact, since the median points are expected to belong to homogeneous area, this information completely characterizes the neighborhood. To asses the proposed approach, we compare it with the traditional approach, based on measurements at the feature points.

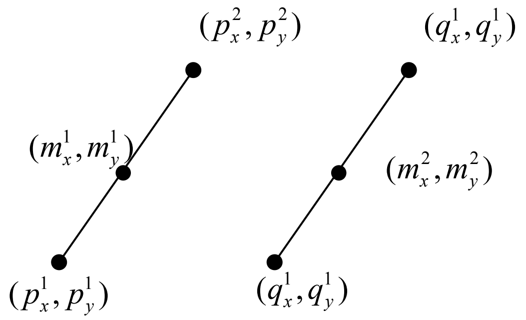

Figure 1. Feature points and median point representation

The proposed approach is called median point matching method and the methods proposed for comparing with it are median neighborhood matching method, point color matching method and the last is a traditional point matching.

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:

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

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

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

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.

The second method utilizes the average color of the median pixels. A pixel has 8 neighbors. For each pixel, the color vectors of its neighborhood are summed and divided with 9. In the end norm of the difference of the color means is calculated with the equation (2).

The third method utilizes the colors of the points $p_i = (p_x^i, p_y^i)$ and $q_i = (q_x^j, q_y^j)$. Now, we will have two norm equations:

$$D(\mathbf{p_1}, \mathbf{q_1}) = \|\mathbf{c}(\mathbf{p}_1) - \mathbf{c}(\mathbf{q_1})\|^2, \quad (4)$$

$$D(\mathbf{p_2}, \mathbf{q_2}) = \|\mathbf{c}(\mathbf{p_2}) - \mathbf{c}(\mathbf{q_2})\|^2, \quad (5)$$

where c($\mathbf{p}_i$), c($\mathbf{q}_i$), are the color vectors for every point $p_i = (p_x^i, p_y^i)$ and $q_i = (q_x^j, q_y^j)$. For the last two methods, the process of comparing the norm with a threshold is the same like in the first method, only the results are different.

The traditional point matching method uses all combinations between the pairs of points for generating solutions and a mean shift estimator is used to find the best estimates from the partial solutions.

IV. TESTING RESULTS

In order to test the performances of the proposed approach, we used image pairs containing a common field of view, obtained for different camera positions and orientations. An example is given in Fig. 2. Corner feature points were selected interactively in both images. All sets of points contained outliers and no correspondence information was used in the estimation. Parameter estimation was carried out with simultaneous approach [1]. The 1D mean shift estimator was used for both methods, with *Epanechnikov* kernels [10]. Estimation scale was set equal with the inter-quartile distance of the data for both methods. The results from the three methods presented above are estimated from nine experiments. The experiments were done with different numbers of points in the images. A constant value of the threshold, T = 10, was used in all experiments reported here. Exception was the case of point color matching method where were two norms that needed to be compared with two different thresholds in the same time. The optimal level of the threshold may be a subject of further study.

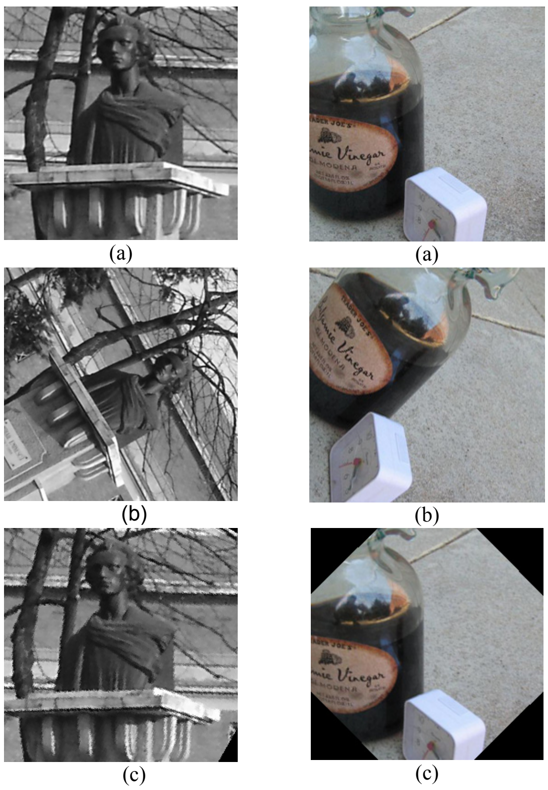

Figure 2. (a) Image from Node1; (b) image from Node 2; (c) image from Node2 after registration.

Graphical results of the tests for all parameter solution vector components are given in Fig. 3-7. Mean and standard deviations of the proposed solutions are given in Table 1.

TABLE I
STANDARD DEVIATION OF ERROR FOR PARAMETER VECTOR COMPONENTS

Method	Angle [s.d.]	Scale [s.d.]	Translation X [s.d]	Translation Y [s.d]
Median point matching	0.0170	0.0313	0.5027	4.5060
Median neighborhood matching	0.0206	0.0262	7.3043	16.7424
Points colors matching	0.0505	0.0319	24.2860	22.4363
Point matching	1.1590	0.0133	32.1852	30.5816

The first method presented good results in all the tests having the highest accuracy. This is especially the case of the angle, horizontal translation and time estimate. The worst case for the proposed method is vertical translation estimate and scale estimate, but it still outperforms the point matching method with infinite threshold (that is without matching). A good result for scale estimate results from the point matching with infinite threshold. As it can be seen from the table I and from the graphics the median point matching method has advantage over the median neighborhood matching method and over the other methods.

TABLE II
STANDARD DEVIATION OF ERROR FOR THE TIME VECTOR

Method	Time T [s.d]
Median point matching	0.0833
Median neighborhood matching	2.7565
Points colors matching	1.0730
Point matching	16.2964

The average computing times in our experiments are given in Table 2. It can be seen that the median point matching method results in a decrease of the computing time (combinatorial dependence of the computing time on the number of points).

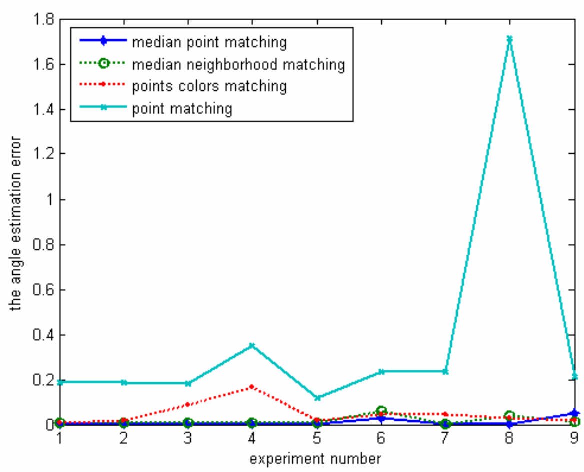

Figure 3. The angle estimation error.

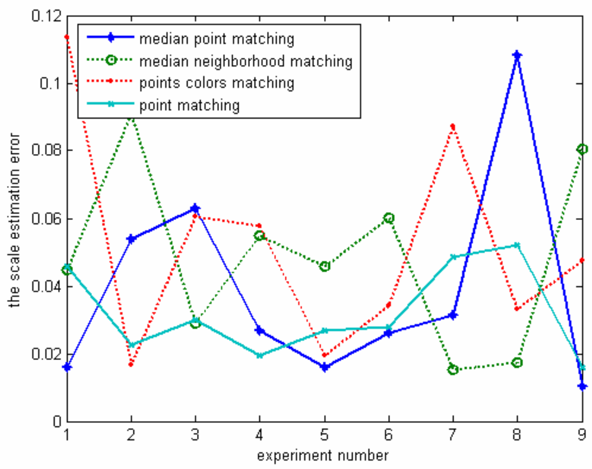

Figure 4. The scaling factor error.

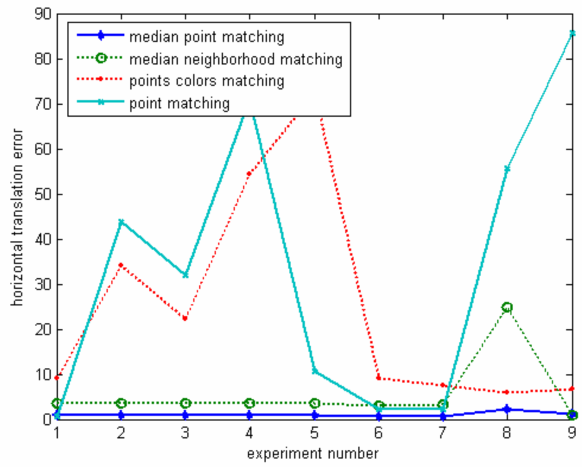

Figure 5. Horizontal translation error.

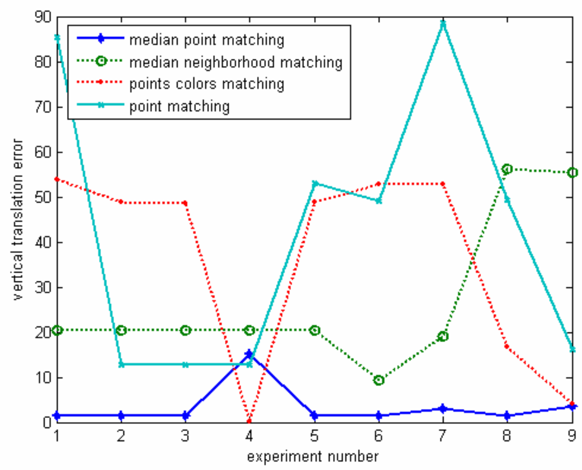

Figure 6. Vertical translation error.

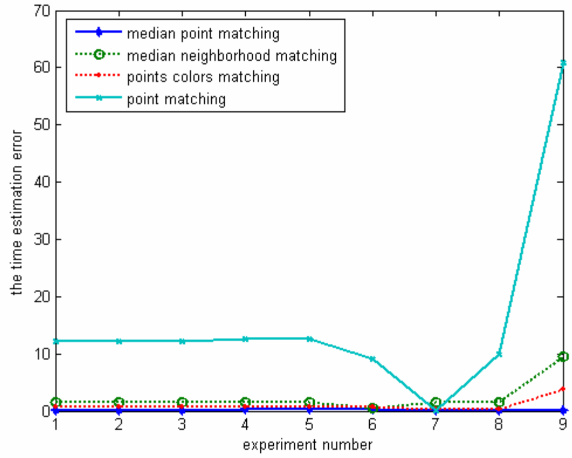

Figure 7. The time factor error

V. CONCLUSIONS

This paper investigates the usefulness of a new point matching method, called median point matching, in image registration. The method is part of an image processing tool developed for video sensor localization in Wireless Sensor Networks. Taking advantage of the smoothness property of median points, the proposed method is less sensitive to noise and gives better results than traditional methods based on measurements made in neighborhoods of the feature points. The proposed method has a low computational cost. Tests have shown that additional smoothing is not needed and is not beneficial in median matching. Finding an image-adapted optimal threshold in feature matching may be a subject of future work.

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