Feature Point Matching Based on Local Relative Velocity Consensus

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Abstract. Feature matching is still a crucial and challenging problem in image processing. In this paper, a novel feature matching algorithm based on local relative velocity consensus (LRVC) is proposed to find two accurate matched feature points. To remove the outliers accurately and robustly, the relative velocity between the putative matches and their corresponding neighbors are exploited. Based on the consensus of relative velocity and the consensus of neighborhood elements, the similarity of each putative matches is evaluated. With a two iteration outlier removal strategy, the feature points are matched accurately and robustly. In the experiment, VGG dataset are used to verify the accuracy and robustness of the proposed method LRVC. The matching results indicate that our method is superior to three other classic feature matching methods.

1. Introduction
Feature point based image processing is efficient and powerful in image registration, content-based image retrieval, object detection and object tracking, SLAM, change detection[1][2].

To find the accurate corresponding feature points, feature matching usually consists of two steps: putative correspondences establishment and outlier removal. Firstly, feature points are extracted with local feature descriptors e.g. scale invariant feature transform (SIFT)[3]. Then based on the nearest neighbor distance ratio (NNDR) between the feature descriptors, the putative correspondences are established. To improve the performance of feature detector and descriptor, GLOH[4], KAZE[5], Daisy[6], SURF[7] are proposed. However, if the images are taken with different cameras, at different time, from different viewpoint, it is inevitable that false matches are reserved in the putative correspondences.

Although, numerous methods are proposed to remove outliers and find two exactly matched point sets. Sometimes they can remove the outliers efficiently. It is still hard for them to remove the outliers with pseudo-isomorphic structures.

In this paper, a novel feature matching method based on local relative velocity consensus (LRVC) is proposed to improve the accuracy of feature matching. Based on the relative linear vector, the relative linear velocity are quantized. Then, the feature point matching problem is solved as a problem to find the correspondences with relative velocity consensus and neighborhood elements consensus.
The rest of the paper is organized as follows: A brief review of related works is presented in Section 2. Section 3 describes the local relative velocity consensus based feature matching method. Section 4 gives the experiment result. In Section 5, we outline our conclusions.

2. Related Work

Feature point matching methods are roughly divided into two categories, the transformation model estimating based methods, and the structure consistency based methods.

Based on transformation model estimation, many methods are proposed. Random Sample Consensus (RANSAC) algorithm[8] is widely used feature matching method. It estimates parameters of a mathematical model from a set of observed data containing outliers iteratively. It produces a reasonable result only with a certain probability as it is a nondeterministic algorithm. With heavy outliers, RANSAC may not be robust enough to yield a desirable results. Iterative Closest Point (ICP)[9] is another remarkable feature matching algorithm based on geometric transformation estimation. To find the closest point on geometric entity to a given point, ICP estimated the geometric model iteratively. Relying on the initial rotations and translations, it have difficulty to match features accurately.

Based on local structure consistency, many methods are proposed. Eliminating the outliers by filtering with mean distance between nearest neighbors, Aguilar et al.[10] proposed Graph Transformation Matching (GTM) to obtained two coincident graphs. Liu et al.[1] designed Restricted Spatial Order Constraint (RSOC) which took the order of neighbors around the corresponding features as a string and evaluated the spatial order difference by a cycle string comparing method. Robust Feature Matching Using Spatial Clustering (RFM-SCAN)[2] took the feature matching problem as a spatial clustering problem with outliers. As the method do not need to estimate the transformation parameters iteratively, it is very efficient. However, outliers with the pseudo-isomorphic structures are still difficult to remove.

3. METHOD

In this section, our discriminative feature matching method is introduced to match two feature point set with similar local structures. The putative matches are established by comparing the distance of the closest neighbor with that of the second-closest neighbor of SIFT descriptor in advance. Then the point matching problem is solved as follows.

3.1. Local Relative Velocity

The putative correspondences are obtained with SIFT descriptor and the nearest neighbor distance ratio (NNDR) strategy. As shown in Fig.1(a), \(p_i\) and \(q_i\) are putative correspondences. The stars are their neighbors. The vector between the inliers in blue lines are consensus, while the vector to the outlier in red are obvious distinction.

With physical constraints, the vector between the matched points are supposed to be coincident. So the relative linear velocity and are formulated.

As shown in Fig.1(b), the vector \(v_{ij}\) and \(u_{ij}\) between feature points \(p_i, q_i\) and their corresponding neighbor \(p_j\) and \(q_j\) are defined.
At the beginning, based on the vector $v_{ij}$ and $u_{ij}$, the relative linear vector $\eta_{ij}$ between corresponding points $p_i$ and $q_i$ is defined in Eqs. 1 as follows.

$$\eta_{ij} = \frac{|v_{ij}|}{|u_{ij}|}$$

(1)

Based on relative linear vector $\eta_{ij}$, the relative linear velocity $s_{ij}$ is defined as:

$$s_{ij} = \log(\eta_{ij}) = \log\left(\frac{|v_{ij}|}{|u_{ij}|}\right) = \log(|v_{ij}|) - \log(|u_{ij}|)$$

(2)

3.2. Point Matching With Local Relative Velocity Consensus

To match the feature points based on the local relative velocity, the consensus of local relative velocity are combined with the consensus of neighborhood elements. Then a set of $N$ putative feature correspondences $S = \{(p_i, q_i)\}_{i=1}^N$ from two images, $I$ as the unknown inlier set, its optimal solution is

$$I^* = \arg \min_I C(I; S, \lambda)$$

(3)

The cost function $C$ is defined as:

$$C(I; S, \lambda) = \sum_{i,j} d_1(q_i, q_j) + \sum_{i,j} d_2(v_{ij}, u_{ij}) + \lambda (N - |I|)$$

(4)

Here the first item which stands for the consensus of neighborhood elements is defined as:

$$d_1(q_i, q_j) = \begin{cases} 0, & q_j \in N_{q_i} \\ 1, & q_j \notin N_{q_i} \end{cases}$$

(5)

The relative velocity consensus between local relative vector $v_{ij}$ and $u_{ij}$ is defined as:

$$d_2(v_{ij}, u_{ij}) = \begin{cases} 0, & d(m_{ij}, m) \leq \rho \\ 1, & d(m_{ij}, m) > \rho \end{cases}$$

(6)

Where $d(m_{ij}, m) = \sqrt{(s_{ij} - s)^2}$.

Then based on with local relative velocity consistency, the point matching method is defined in Algorithm 1.
4. EXPERIMENT RESULTS

To evaluate the performance of the proposed algorithm for the matching accuracy and robustness, various real image pairs are applied. VLFEAT toolbox (Vedaldi and Fulkerson 2010) is employed to construct KNN graph and search the $K$ nearest neighbors using K-D tree. The putative correspondences are extracted and matched by comparing the distance of the nearest neighbour with that of the second nearest-neighbour. The ground truth are then checked manually one by one. RMSE, Accuracy, Recall, Precision, Specificity, F-score (Lin, Lin, and Zha 2017) and Time are used as evaluation criterions.

In the experiment, LRVC are compared with RFM-SCAN, RANSAC, RSOC. RFM-SCAN, RANSAC, RSOC are implemented based on the public available source code. To build the KNN graph, the $K$ of RSOC is set to 6. For RANSAC, the distance threshold $t$ for deciding outliers is set to 0.005. For RFM-SCAN, the default parameters of are used. In case of LRVC, the parameters are empirically set as $K = 6, \lambda = 6$ and $\rho = 0.5$.

To illustrate the robustness and accuracy of the proposed method LRVC, the matching results of LRVC on three typical image pairs are compared with that of three feature matching methods. These matching results are presented in Fig.2. Where the green lines indicate the correct matches, the red lines indicate false matches and yellow lines indicate the missed correct matches.

In Fig.2, three image pairs with repetitive patterns, nonrigid deformation are used. The outlier ratios of Bark, Boat and Graf are 25.7%, 48.05% and 50.75% respectively. With repetitive patterns and affine transformation in (a) Bark, more outliers are retained in the matching results of RFM-SCAN and RANSAC, while our LRVC achieves better result. In the matching result of (b) Bark, LRVC saves more inliers with local relative velocity consensus, while RFM-SCAN, RANSAC and RANSAC can not remove the outliers cleanly. The matching result of LRVC on (c) Boat is better than that of other methods. It can be seen that with different type image pair, the proposed LRVC achieves the best results with high precision.

| Algorithm1 Local Relative Motion Consensus |
|---|
| **Input:** putative set $S = \{(p_i, q'_i)\}_{i=1}^{N}$, parameters $K$, $\rho$. |
| **Output:** inlier set $I^*$ |
| 1. Construct neighborhoods $\{N_{p_i, q'_i}\}_{i=1}^{N}$ based on $S$. |
| 2. Calculate $d_1, d_2$ with Eqs.(5) and Eqs.(6). |
| 3. Determine $I_0$ using Eqs.(3). |
| 4. Construct neighborhoods $\{N_{p_i, q'_i}\}_{i=1}^{N}$ based on $I_0$. |
| 5. Calculate $d_1, d_2$ with Eqs.(5) and Eqs.(6). |
| 6. Determine $I^*$ using Eqs.(3). |
In order to demonstrate the performance of the proposed LRVC, 10 image pairs from dataset VGG, including Graf, Wall, Bark and Boat with viewpoint change, repetitive patterns and rotation change are used. The average accuracy, recall, precision, specificity, F-score and running time of the four methods are shown in Table I. It can be seen that with global constraint, the precisions and recall of RSOC keep above 90% with different transformation. But it is slower than other three method. The recall of RANSAC is better. Because of the outliers are likely be retained as inliers by randomly sampling. the precision, specificity and F-score are lower than LRVC and RANSAC. Based on absolute motion consistency, RFM-SCAN is the worst of all. The average of precision, specificity and F-score indicates that our LRVC achieves the best trade-off between recall and precision. The running time is almost the same as RFM-SCAN. But LRVC is faster than RSOC and RANSAC. So it can be concluded that based on local relative velocity consensus, LRVC is more robust and accurate.

Table I: Point matching results of LRVC on VGG dataset against three classic feature matching methods.

|       | LRVC | RSOC | RANSAC | RFM-SCAN |
|-------|------|------|--------|----------|
| RMSE  | 14.95| 40.73| 181.98 | 420.71   |
| Accuracy | 98.87%| 98.00%| 95.40% | 76.60%   |
| Recall | 98.14%| 99.84%| 99.90% | 94.09%   |
| Precision | 99.57%| 96.54%| 91.68% | 72.21%   |
| Specificity | 99.34%| 95.72%| 89.83% | 62.27%   |
| F-score | 98.85%| 98.13%| 95.59% | 80.21%   |
| Time   | 0.07 | 66.00| 1.08   | 0.06     |

5. CONCLUSION
To improve the accuracy and robustness of feature matching, a novel algorithm based on local relative velocity consensus is proposed. Based on the relative velocity between the putative matches and their K nearest neighbors, the relative velocity are defined. Evaluated by the consensus of relative velocity consistency and the consensus of neighborhood elements, a point matching strategy is designed. Tested with VGG datasets, the average of F-score indicates that our LRVC achieves the best trade-off between recall and precision. Compared with three feature matching methods, it can be concluded that our LRVC are more robust and accurate.
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