# Region-constrained Feature Matching with Hierachical Agglomerative Clustering

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Abstract: Local feature matching is one of the most fundamental issues in computer vision. Hierarchical agglomerative clustering (HAC) has been effectively used to distinguish inliers from outliers. The drawback of HAC is its large computational complexity which increases rapidly as the number of feature correspondences increases. To overcome this drawback, this paper proposes a region-constrained feature matching in which an image is segmented into small regions and feature correspondences are clustered inside each region. Adjacent segmented regions are merged to form larger regions if the correspondences inside regions are similar. The merge may increase the accuracy of clustering, and consequently, it improves the accuracy of matching operations as well. The proposed region-constrained clustering dramatically reduces the execution time by as much as 500 times compared to the previous clustering while it achieves a similar matching accuracy.

## 1 INTRODUCTION

Due to a popular use of high-resolution image sensors, high-definition (HD) images are widely available in high-resolution CCTV cameras and broadcasting cameras as well as mobile devices such as mobile phones. A large amount of data in an HD image requires a large computing power to process image search, classification and recognition. Local feature matching has been one of the widely used techniques for object recognition. Hierarchical agglomerative clustering (HAC) has been effectively used to distinguish inliers from outliers but it suffers from its large computational complexity which increases rapidly as the number of feature correspondences increases. To reduce the computational complexity of HAC, this paper proposes a region-constrained feature matching in which an image is segmented into small regions and feature correspondences are clustered inside each region.

Local invariant features have been widely used for image recognition because they are robust in noise, light variation, and viewpoint change (Lowe, 2004; Bay et al., 2008; Rosten et al., 2010). Image recognition based on local feature matching is performed by finding the correspondences between local features in different images. The local feature matching has been used in a number of applications, such as image stitching, 3D reconstruction, and object identification. To find similarities between features, Euclidean distance is calculated between the feature vectors and the nearest neighbour descriptor is selected or the distance ratio between the nearest neighbour descriptor and second nearest descriptor is used. The correspondence using only similarity of feature vector may not always result in the correct correspondence because comparison of local patch may find partial similarity between descriptors. Therefore, differentiation between correct correspondences (inliers) and incorrect correspondences (outliers) is needed. Hence, effective methods to distinguish the inliers from the outliers have been extensively investigated.

In (Lowe, 2004), an image is assumed to be a rigid scene, and RANSAC (RANdom SAmple Consensus) is used to fit a model to experimental data and to reject inconsistent matches. However, this method is not effective in the case of non-rigid image deformation or complicated scene which cannot be represented by an affine transform. A number of image feature matching studies for non-rigid image deformation have been conducted. One promising approach for non-rigid image matching is

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a use of the geometric information among local features. These approaches find corresponding pairs or triplets of points in the graph consisting of features with properties of the distance and angle between feature points in the image which generally remains unchanged. This matching is performed by considering the spatial layout between keypoints. If there are many correspondences in an image, the property of the invariant distance and angle can be generated by a combination of mismatched points. Therefore incorrect matching results can be generated. In addition, this graph matching method requires its computational complexity increasing exponentially as the number of feature points increases (Gomila and Meyer, 2003; Duchenne et al., 2011; Torresani et al., 2008).

Another approach for improved non-rigid image matching uses clustering to get reliable feature set (Cho et al., 2009). This approach repeatedly performs clustering with all the feature correspondence in an image until all inter-cluster similarity is larger than the intra-cluster similarity. Although this method successfully improves the accuracy of matching results, it also suffers from a rapid increase of the computational complexity with the increase of the number of correspondences. As a result, a fast algorithm to reduce the complexity is necessary for a practical use.

This paper proposes a novel feature matching algorithm that reduces the computational complexity of the clustering-based outlier exclusion. The proposed algorithm segments an image into small regions and performs clustering only inside the candidate region. Adjacent segmented regions are merged to form larger regions if the correspondences inside regions are similar. The merge may increase the accuracy of clustering, and consequently, it improves the accuracy of matching operations as well. As the proposed algorithm uses only candidate regions for clustering while the previous clustering algorithm uses the whole image, the increase of the complexity of the proposed algorithm is much less than that of the previous algorithm.

This paper is organized as follows. Related works are introduced in Section II and the proposed feature matching algorithm is proposed in Section III. Section IV presents experimental results and Section V concludes this paper.

## 2 RELATED WORKS

This section describes HAC (Hierarchical Agglomerative Clustering) algorithm which is used as the base clustering algorithm in this paper (Friedman et al., 2009). Figure 1 depicts the flow of a general clustering algorithm. The first step (Correspondence extraction) generates the features that characterize the object to recognize. In the second step (Cluster similarity), similarities between features are measured. These similarities are used for clustering in the next step, and then these two steps are performed repeatedly until all inter-cluster similarity is larger than intra-cluster similarity.

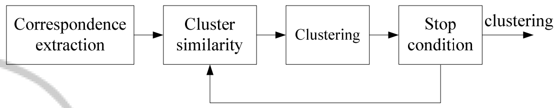


Figure 1: A general flow of a clustering algorithm.

HAC is one of the clustering algorithms that adopts the same flow as Figure 1. A brief description of HAC is given as follows (Xu et al., 2005).

```
HAC Algorithm

Step 1: Determine all inter-
        correspondence similarities
Step 2: Select two closest
        correspondences or clusters and
        form a cluster
Step 3: Redefine similarities between
        the new cluster generated in
        Step 2 and the other
        correspondences or clusters
Step 4: Return to Step 2 until inter-
        cluster similarity is larger
        than intra-cluster similarity
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For a formal definition of geometric similarity, the distance between two matches $m_i$ and $m_j$ is defined next. Let $p$ and $q$ be two keypoints in different images matched by homography $h_i$. Let $x_i$ and $x_i'$ denote the respective positions of keypoints $p$ and $q$. Let the match between $p$ and $q$ be denoted by $m_i = (x_i, x_i', h_i)$. Between two feature correspondences $m_i = (x_i, x_i', h_i)$ and $m_j = (x_j, x_j', h_j)$, the distance is defined as follows (Cho et al., 2009):

$$d(m_i, m_j) = \frac{1}{2}(d(m_j|m_i) + d(m_i|m_j))$$
$$d(m_j|m_i) = \frac{1}{2}(|x_j' - h_i x_j| + |x_j - h_i^{-1} x_j'|) \quad (1)$$
$$d(m_i|m_j) = \frac{1}{2}(|x_i' - h_j x_i| + |x_i - h_j^{-1} x_i'|)$$

where $|\cdot|$ denotes Euclidean distance.

Let $G$ and $H$ represent two clusters of matches. Then, the dissimilarity between the two clusters is defined as the distance between closest matches of the two clusters.

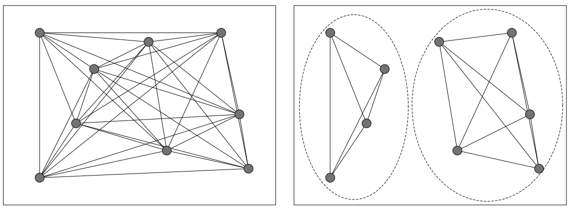
$$D(G,H) = \min_{\forall m_i \in G, \forall m_j \in H} d(m_i, m_j) \tag{2}$$

# 3 THE PROPOSED ALGORITHM

This section proposes a HAC-based clustering algorithm that attempts to reduce the computational complexity without a significant decrease of matching accuracy. The algorithm is developed under the assumption that SIFT is used as the local feature. To reduce the computational complexity of HAC, an image is segmented into small regions and feature correspondences are clustered inside each region. Adjacent segmented regions are merged to form larger regions if the correspondences in the adjacent regions are similar. The merge may increase the accuracy of clustering, and consequently, it may improve the accuracy of matching operations as well.

## 3.1 Region-Constrained Clustering

This paper proposes a region-constrained clustering that sets the candidate regions with similar attributes and perform clustering with feature points inside the candidate regions.



(a) (b)

Figure 2: (a) HAC. (b) Region-constrained clustering.

Figure 2 shows the difference between the original HAC and region-constrained clustering. The dashed-ellipse in Figure 2(b) indicates the candidate regions. Both methods use the same feature points, however region-constrained clustering perform clustering only for feature points within the candidate regions.

## 3.2 Geometric Relationship in Correspondences

Let P and Q denote a set of local features obtained from two images, respectively. Feature vectors $p_u$, $q_v$ from two feature set P, Q are respectively represented by

$$p_u = [(x_u, y_u), \sigma_u, \theta_u, f_u] \tag{3}$$

$$q_v = [(x_v, y_v), \sigma_v, \theta_v, f_v] \tag{4}$$

where $(x_u, y_u)$ indicate coordinates of the corresponding keypoint position, $\sigma_u$ and $\theta_u$ is the scale and orientation information. $f_u$ is a feature vector, called descriptor.

Initially, correspondences are evaluated by comparing the distance of the closest neighbour to that of the second-closest neighbour (Lowe, 2004). From these initial correspondences, the geometric similarity homography for each correspondence is used to perform HAC inside each region. The similarity is estimated from a pair of SIFT descriptors for a given correspondence. Each SIFT descriptor carries information about the scale and orientation. Thus, the homograph matrix for a correspondence can be expressed as the product of matrices with the scale, rotation and translation information.

$$\begin{aligned} h &= [S(\Delta\sigma)][R(\Delta\theta)][T(\Delta x, \Delta y)] \\ &= \begin{pmatrix} \Delta\sigma & 0 & 0 \\ 0 & \Delta\sigma & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} cos\Delta\theta & -sin\Delta\theta & 0 \\ sin\Delta\theta & cos\Delta\theta & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 1 & 0 & \Delta x \\ 0 & 1 & \Delta y \\ 0 & 0 & 1 \end{pmatrix} \end{aligned} \tag{5}$$

where $\Delta\sigma = \sigma_v/\sigma_u$ , $\Delta\theta = \theta_v - \theta_u$ and $\Delta x$ , $\Delta y$ are given as follows.

$$\Delta x = x_v - (\Delta\sigma \cos\Delta\theta x_u - \Delta\sigma \sin\Delta\theta y_u) \tag{6}$$

$$\Delta y = y_v - (\Delta\sigma \sin\Delta\theta x_u + \Delta\sigma \cos\Delta\theta y_u) \tag{7}$$

## 3.3 Constrained Region

The area of the region may affect the accuracy and complexity of the proposed algorithm. It is often the case that object segmentation results in an image with over-segmented regions. In this case, the clustering constrained by the over-segmented regions may not reflect the nature of the correspondence. Therefore, this subsection proposes an algorithm that merges the over-segmented regions into large regions if they are turned out to be similar regions. The merge of regions may improve the accuracy of feature matching operations.

### 3.3.1 Region Homography Matrix

The segmented regions generated by a segmentation algorithm such as watershed transform needs to be merged and then used as candidate regions for clustering. This paper defines the homography matrix of each region and by using the similarity of homography matrix, it merges a set of regions which are likely to be used to constrain the boundary of a clustering operation inside the region.

From the homography of a feature correspondence given by (5), the homography of a region correspondence is defined as the regional average homography of feature correspondence. The formal definition is given as (8). If there exist $m$ feature correspondences in the area $A_i$ the area homography of $A_i$ is formulated as the product of the average ratios of the scale, the differences of rotation and translation.

$$H_i = \mathrm{S}\left(\sum_{j=1}^{m} \Delta\sigma_j\right)\mathrm{R}\left(\sum_{j=1}^{m} \Delta\theta_j\right)\mathrm{T}\left(\sum_{j=1}^{m} \Delta x_j, \sum_{j=1}^{m} \Delta y_j\right) \quad (8)$$

### 3.3.2 Region Similarity

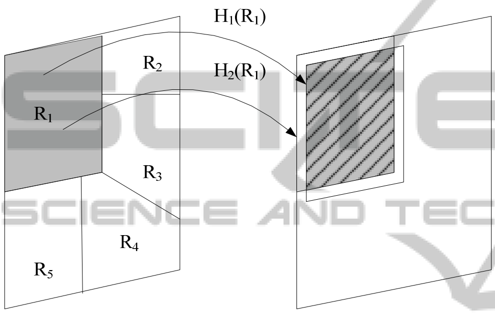



Figure 3: Region homography projection.

This subsection discusses a method to measure the similarity of the region homography matrices. Suppose that the two adjacent regions $R_1$ and $R_2$ in Figure 3 have region homographies $H_1$ and $H_2$, respectively. If there is a similarity between $H_1$ and $H_2$, the regions projected by $H_1$ and $H_2$ must be similar, that is, the two projected regions must be largely overlapped. Based on the above observation, the similarity measure between two homographies is derived from the overlapped region.

The overlapped region may be affected by the area and shape of the region. To avoid this affect, this paper defines an overlapping criterion that is insensitive to the area and shape of a region. To this end, a circle with the fixed size (corresponding to radius 30), is used for the similarity measure. This circle is called the unit circle ($UC$) hereafter in this paper. Note that a similar idea has been used in (Mikolajczyk et al., 2005) to measure the matching score in affine region detectors.

Region $R_i$ projected by $H_i$ is expressed by the product of two matrices. Matrix $X_i^T$ is defined to represent all the pixels in region $R_i$.

$$X_i^T = [x_i, y_i, 1] \text{ where for all } (x_i, y_i) \in R_i \quad (9)$$

The region projected by $H_i$ is defined as follows:

$$X_{i'} = H_i X_i \quad (10)$$

For two adjacent regions $R_i$, $R_j$ having homography $H_i$, $H_j$, respectively, the region similarity between the regions are formulated as follows:

$$\text{Region similarity}(R_i, R_j) = \begin{cases} 1, & H_i X_i \cap H_j X_i \neq \emptyset \\ 0, & H_i X_i \cap H_j X_i = \emptyset \end{cases} \quad (11)$$

where $X_i$ represents the matrix representing all points in $UC$, that is $X_i^T = [x_i, y_i, 1]$ where for all $(x_i, y_i) \in UC$.

In the above definition, similarity is "1" when the two projected regions are overlapped. It is "0", otherwise. When the region similarity is "1", then the corresponding two regions are combined to make a new region $R_1' = R_1 \cup R_2$ for the independent clustering operation.

The clustering accuracy is large when the number of the inliers is larger than that of the outliers in each region. The proposed algorithm increase the accuracy by merging regions for the case when the number of correspondences in over-segment region is too small. Furthermore, the results of the clustering operation inside a single region becomes reliable when the regions are composed of a set of similar homographies because the clustering operations use the homography similarity between correspondences.

For a reduction of computational complexity, region merge is performed only among adjacent regions. To this end, the segmented regions are expressed by a graph which is commonly used data structure for representing partitions (Kim et al., 2010). Using this graph, the detection of adjacent regions is easy to perform.

### 3.3.3 Complexity Analysis

Figure 4 shows the flow of the proposed algorithm which segments an input image into small regions to constrain the clustering operation. Using the result of the initial correspondence, regions are merged to form large regions. Then, HAC is performed for correspondences in each region. The final clustering result is obtained by collecting all the HAC results in every region.

With a pair of N correspondences, conventional HAC requires the construction of at most $N-1$ clusters, and so $N-1$ iterations (Step 2, 3, and 4) are required. In addition, $O(N^2)$ operations are required in order to compute the similarity between clusters. Therefore, the complexity is $O(N^3)$. On the other

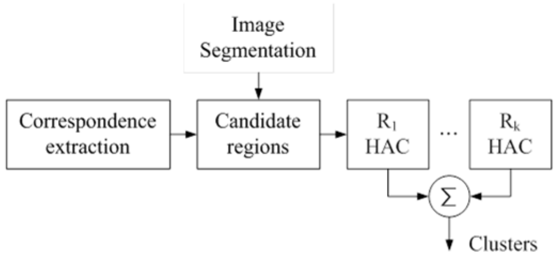



Figure 4: The flow of the proposed clustering algorithm.

hand, the complexity of the proposed algorithm depends on the number of regions. Suppose that an image is segmented into k regions. Let $n_1, n_2, \cdots, n_k$ denote the number of correspondences in the k regions. Then, equations (12) and (13) are true. Note that the computational complexity of the i<sup>th</sup> region is $O(n_i^3)$. Equation (13) proves that the proposed algorithm requires much less complexity than that the conventional HAC does.

$$\bigcup_{i=1}^{k} n_i = n \,, where\ n_i \cap n_j = \emptyset \tag{12}$$

$$n_1^3 + n_2^3 \cdots n_k^3 \ll n^3 \tag{13}$$

## 4 EXPERIMENTAL RESULTS

Experiments are conducted with two dataset with shared contents. One is the eccv dataset used in (Ferrari et al, 2006) that consists of 9 model objects and 23 test images with a relatively small number of correspondences. The other is Oxford dataset that has been used for performance evaluation of affine area detectors and local descriptors. The data sets consist of images which are distorted by various degradation (viewpoint change, image blur, JPEG compression artifacts and illumination change). Oxford dataset includes homography mapping between the reference and distorted target images that give the ground truth correspondences. These dataset images are large and complex, composed of a large number of correspondences.

The initial correspondences are generated using the method of NNDR in (Lowe, 2004). Initial correspondece and segemtation results are used to derive candidate areas. Figure 5 shows the candidate areas obtained by the proposed algorithm with Graffiti image of Oxford dataset. As shown in Figure 5(b), different candidate areas are represented by different colors. The white colored areas includes one or no correspondence, and therefore, they are excluded from the clustering operations because clustering needs at least two correspondences to calculate similarity between correspondences.

(a) (b)

Figure 5: Candidate areas for clustering over Graffiti image. (a) Original image. (b) Candidate areas with colors representing segmentation results.

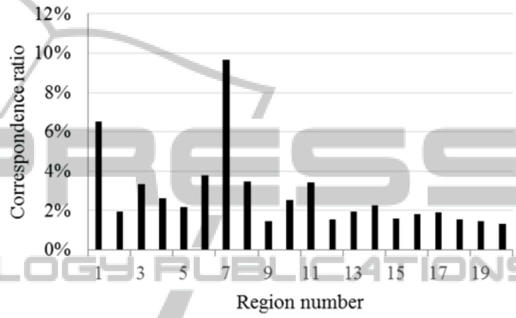



Figure 6: The ratio of each candidate area correspondences against the total correspondences over Graffiti image.

Figure 6 shows the ratio of the number of correspondences in the candidate area and the number of correspondences in the whole image. This figure shows only the 20 candidate areas with the most correspondences. The result shows that the ratio is less than 10% for all candidate areas. Recall that the complexity is reduced when the number of correspondences in each area is small (see (13)). Therefore, the calculation time can be significantly reduced.

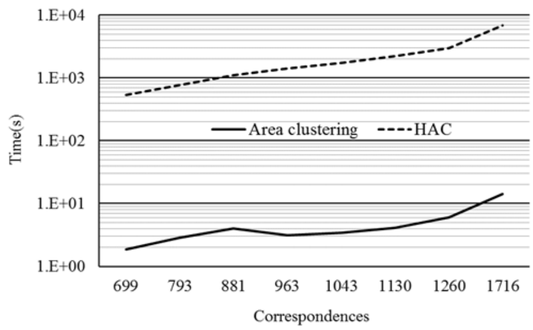



Figure 7: Comparison of execution time between area clustering and HAC.

Figure 7 shows the execution time according tothe number of correspondences using Oxford Graffiti dataset. The horizontal axis represents the number of correspondences, which is generated by NNDR. The vertical axis represents the execution time in the logarithmic scale. The execution time is measured using a single-core Intel i5-750 processor running at 2.67Ghz. With an increasing number of correspondences, the difference between area clustering and the HAC increases dramatically. Note that the execution time of the area clustering includes segmentation algorithm that generates candidate regions.

Table 1: Recognition results over Oxford dataset.

| | Bikes | Graffiti | Boat | Leuven |
|---|---|---|---|---|
| Propose cluster size | 733 | 1055 | 2131 | 1096 |
| Proposed Matching score | 72.7% | 67.7% | 78% | 78.8% |
| HAC cluster size | 886 | 1056 | 2133 | 1189 |
| HAC Matching score | 65.4% | 67.8% | 76.3% | 74.9% |

Table 1 shows the accuracy of the proposed clustering and the HAC. In order to evaluate the accuracy, the value of the matching score is used, which is often used as the metric in feature matching algorithms (Mikolajczyk et al., 2005). For this experiment, Oxford dataset is used with several hundred initial feature correspondences in each image pair. In all dataset images, the values of the affine transform are presented. The proposed algorithm gives a matching score higher than the original HAC. The cluster size of the proposed algorithm is the sum of each candidate region's clustering results. Although the cluster size is reduced when compared to HAC, the proposed algorithm achieves the higher matching score. This indicates that the proposed algorithm effectively removes outliers.

Figure 8: Models used in Figure 9.

Figure 8 shows the models in the test images shown in Figure 9 which shows the correspondences obtained from the experiments with the dataset that has been used in (Ferrari et al, 2004). Figure 9 (a), (c), (e), and (g) show the experimental results of HAC whereas Figure (b), (d), (f) and (h) show the results obtained by the proposed algorithm. The blue circles show the correspondences which have been determined to be inliers by clustering. The number of clusters in the proposed algorithm is small but inliers are only on the object. The candidate area clustering is not affected by the correspondences in the other area, and therefore, the possibility of forming a cluster by outlier is reduced.

For the evaluation of the recognition accuracy, the recall and precision rates are evaluated. Recall and precision are based on the number of correct and false matches between two images. Among positive and negative matches, there are four possibilities, TP (True Positive), FP (False Positive), TN (True Negative), and FN (False Negative). Recall and Precision are defined as follows:

$$recall = \frac{TP}{TP + FN} \tag{14}$$

$$1 - precision = \frac{FP}{(TP + FP)} \tag{15}$$

Table 2 shows the precision and recall of figure 9. Generally, the precision of the proposed algorithm is high. However, the recall is less than the original HAC because the proposed algorithm performs clustering with only feature points in the candidate region.

Table 2: Recall and precision of the pairwise object matching on eccv dataset in Figure 9.

| | (a)(b) | (c)(d) | (e)(f) | (e)(h) |
|---|---|---|---|---|
| Proposed cluster size | 51 | 79 | 340 | 100 |
| Proposed recall | 0.71 | 0.71 | 0.85 | 0.67 |
| Proposed precision | 0.96 | 0.95 | 0.99 | 0.95 |
| HAC cluster size | 78 | 124 | 408 | 120 |
| HAC recall | 0.81 | 0.92 | 0.97 | 0.70 |
| HAC precision | 0.72 | 0.78 | 0.95 | 0.83 |

# 5 CONCLUSIONS

This paper proposes a region-constrained clustering algorithm for outlier identification. An image is segmented into small regions with similar geometric properties and then HAC is performed with correspondences only inside every region. The possibility of incorrect clustering by the correspondence outside the region is reduced. The proposed algorithm is faster when compared to the conventional HAC, as in the conventional HAC, the complexity exponentially increases with the increase of the input data size. Therefore, the proposed algorithm is effective in an image with dense correspondences.

The proposed algorithm uses region similarity to merge regions to increase the region of clustering operation and the accuracy of the clustering result. Future research may investigate an effective merge algorithm.

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## APPENDIX


Figure 9: HAC versus area clustering (a),(c),(e),(g) show the results by HAC (b),(d),(f),(h) show the results by the proposed area clustering.