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Feature Guided Biased Gaussian Mixture Model for image matching

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ABSTRACT

In this article we propose a Feature Guided Biased Gaussian Mixture Model (FGBG) for image matching. We formulate the matching task as a Maximum a Posteriori (MAP) problem by seeing one point set as the centroid of a Gaussian Mixture Model (GMM) and the other point set as the data. A Thin Plate Spline (TPS) transformation between the two point sets is learnt so that the GMM can best fit the data. Our main contribution is to assign each Gaussian mixture component a different weight. This is where our model differs from the traditional Self Governed Balanced Gaussian Mixture Model (SGBG), whose Gaussian mixture components have equal coefficients. The new weight is defined as a value related to feature similarity, which can be computed by simply decomposing a distance matrix in the feature space. In this way, both feature similarity and spatial arrangement are considered. The feature descriptor is introduced as a reasonable prior to guide the matching, and the spatial transformation offers a global constraint so that local ambiguity can be alleviated. We solve this MAP problem in a framework similar to [16], in which Deterministic Annealing and the Expectation Maximization (EM) algorithms are used. We show that our FGBG algorithm is robust to outliers, deformation and rotation. Extensive experiments on self-collected and the latest open access data sets show that FGBG can boost the number of correct matches.

1. Introduction

Finding corresponding points between two images is one of the fundamental problems in computer vision and is a key ingredient in a wide range of applications including model fitting [19,45,56], motion estimation [7,55], shape recovery [58,41,20], object recognition [15,37,13] and 3D reconstruction [21,2], etc. Corresponding points are the projections of the same scene point and can be Harris/DoG corners or SIFT features in real applications. However, image feature point matching is not an easy task for two reasons: (1) The extracted features contain many outliers and only a small portion of them could be correctly matched. (2) The transformation between these points is complex due to the projection of 3D world points at different depth to the 2D image plane. Consequently the matching results are either too sparse or with too many mismatches. In this article we propose a new method that considers both pairwise feature similarity and overall spatial alignment to address the image feature point matching problem. On the one hand, the correct feature matches can provide

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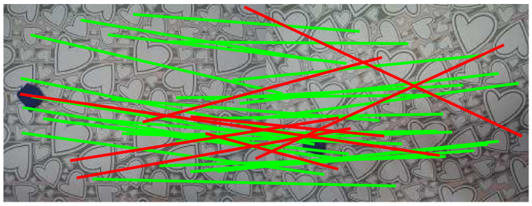
reasonable guidance for the spatial alignment even though the transformation is complex and many outliers exist. This is intuitive because usually outliers have much lower feature similarity than inliers. It will be easier for the algorithm to handle complex transformation under the guidance of feature similarity. On the other hand, the spatial arrangement based method requires the motion to be regularized, which can rectify the mistakes in the feature space. The method penalizes the smoothness of the transformation so that neighboring points should move coherently. Compared with correct matches, wrong matches are disorganized. Even though a wrong feature matching with high similarity score provides a wrong guidance, it is still expected to be rectified by the motion constraint.

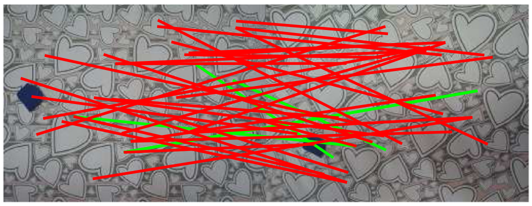
Fig. 1 is a simple example of our method. We consider two images of a scene with repeated patterns. SIFT key points and their descriptors are extracted. We then match them using (a) SIFT [53], (b) RPM [17] and (c) our FGBG algorithm. As the recurring patterns produce many local similar regions, the local feature descriptor based matching method such as SIFT will not work well. From Fig. 1 we can see that mismatches of SIFT relate two parts which have similar local appearance but are globally irrelevant. RPM is unable to find correct matches due to large geometry changes and outliers in the original SIFT feature points. Our method not only finds the most correct matches, but also acquires satisfactory precision. This shows that our thinking of using feature similarity to guide the matching procedure while imposing spatial arrangement constraint is feasible, and can enhance the result.

The Gaussian Mixture Model for point sets registration has been studied for a long time. It treats one point set as the centroid of the GMM and points from the other point set as the data described by this GMM. However, in previous work each model point is assigned the same Gaussian mixture coefficient. Thus a data point can move to any model point with equal chance. We refer to this kind of method as Self-Governed Balanced GMM (SGBG). "Self-Governed" means that it relies on nothing but the spatial arrangement of the points themselves, and the word "Balanced" indicates that all the GMM components are assigned equal weights. However, even though the SGBG algorithm has achieved great success in point set registration, it suffers from the following cases due to the lack of other information except for the spatial arrangement: (1) When the point set contains a high ratio of outliers. In the context of image matching, the initial features usually contain a large



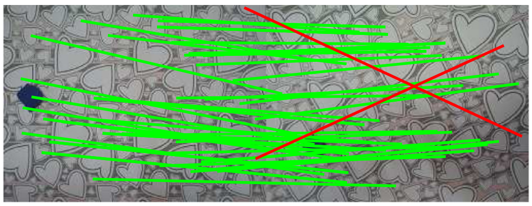
TP: 27 TN: 8

(a) SIFT [53]



TP: 4 TN: 70

(b) RPM [17]



TP: 50 TN: 2

(c) FGBG

Fig. 1. Illustration of our basic idea. From top to bottom: matching using SIFT [53], matching using RPM [17] and matching using our method. True Positives (TP) are in green and True Negatives (TN) are in red. (a) The images present several repeated patterns so that SIFT will mismatch these local similar parts. (b) Due to outliers and geometry differences, the RPM algorithm is unable to find correct matches. (c) Our idea of combining feature similarity with spatial arrangement can enhance the result. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)