Rejecting mismatches between fish-eye camera images by RVM

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Abstract

Establishing reliable correspondence points is a fundamental problem in computer vision. In this work, we studied mismatch-rejecting between two fish-eye camera image by RVM learnings. The fundamental idea that, for given two fish-eye images of a scene, the corresponding points constitute a manifold in joint-image space $R^4$, and outliers can be detected by checking whether they are consistent with the upward views of the manifold. Experiments on real image pairs demonstrate the excellent performance and feasibility of our proposed method.

1. Introduction

The Panoramic vision is attracted more and more interest of researchers[4,5]. And Panoramic vision techniques has been studied and applied in many aspects, for example, mobile robots navigation[1], localization[4] and map building[2,3].

This work studied mismatch-rejecting from given putative correspondences between two fish-eye camera images. Establishing reliable correspondences points is a fundamental problem in computer vision [6,7]. For given images, correspondences points are the projection of the same point in the scene. The putative correspondences are usually established by matching the interest points with local information, for example, the intensity in a small region around the interest points, or some kind of local descriptor [8,9]. However, usually a large proportion of the putative correspondences are outliers due to viewpoint change, occlusion, local ambiguity, etc. And the outliers are usually enough to ruin the traditional estimation methods. Therefore, much of the endeavor in computer vision community is to overcome or alleviate this problem by rejecting the outliers, and many methods are introduced, for example, RANSAC (RANdom SAmple Consensus) [10,11], LMedS (Least Median of Squares) [12,13], MLESAC [14,15].

We focus on rejecting outliers by Correspondence View (CV)[16]. For given two images $I$ and $I'$ of a scene, fundamental idea of CV is that corresponding points between them constitute a manifold $M_c : F(p, p') = 0$ in joint-image space $R^4$, where $p \in I$ and $p' \in I'$. CVs are two upward views $f$ and $f'$ of $M_c$, which are the scenario when we stand on $I$ and $I'$ respectively to observe $M_c$.

The important is that correct corresponding points should be consistent with at least one of the two CVs and outliers can be detected by checking whether they are not consistent with both CVs. This work studies CV learning and outliers rejecting by Relevance Vector Machine. Experiments on real image pairs demonstrate the excellent performance of our proposed RVM-CV learning method and its superiority.

The remainder of this paper is organized as follows: in the next section, the related works on correspondence view (CV) will be briefly reviewed, and the fundamental idea to reject outliers will be introduced. In section 3, we give our learning method for CV. In section 4, we study the performance of our proposed method experimentally. Conclusion is made in section 5.

2. Related works and fundamental ideas to reject outliers

Given two fish-eye camera images $I : U \times V$ and $I' : U' \times V'$. Correspondence points are the point pair in two images that are the projection of same scene point. Based on the theory of correspondence manifold, correspondence points between two images lie on a manifold $M_c$ (correspondence manifold [16]) in joint image space $R^4$ [17]. Correspondence view

$$f(u, v) = (g_1(u, v), g_2(u, v)) = (u', v')$$

(1)

and

$$f'(u', v') = (g_1'(u', v'), g_2'(u', v')) = (u, v)$$

(2)

are the upward views of correspondence manifold $M_c$, where $(u, v) \in I$ and $(u', v') \in I'$. Correct corresponding points should satisfy at least one of the two views $f$ and $f'$. Mismatches can be rejected by checking whether they are consistent with the correspondence view $f$ or $f'$, and the consistency, for example a putative correspondence $(u, v, u', v') \in I \times I'$ with correspondence view $f$, can be defined as: if $(u, v) \in I$ and $(u', v') \in I'$ satisfy $g_1$ and $g_2$, then we say $(u, v, u', v')$ is consistent with $f$, and the consistency of $(u, v, u', v') \in I \times I'$ with correspondence view $f'$ can be defined similarly. However, we do not know
real \( \{g_i, g'_i, i = 1, 2\} \) in practice. Therefore, the key is how to estimate them in applications.

3. Learning CV

3.1. Subspace projection

Given a set of putative point correspondences

\[ S = \{(p_i, p'_i) = (u_i, v_i, u'_i, v'_i), i = 1, \cdots, n \} \subset I \times I': U \times V \times U' \times V'. \]  

(3)

If a given correspondence point pair

\[ (p, p') = (u, v, u', v') \in I \times I' \]

satisfies \( f = (g_1, g_2) \), then its projection \( (u, v, u') \) on space \( U \times V \times U' \) is consistent with \( g_1 \). Therefore, the projection

\[ S_{U \times V \times U'} = \{(u, v, u')|(u, v, u', v') \in S\} \]

(4)

of \( S \) can be regarded as a sample set from \( u' = g_1(u, v) \).

In this work, we will estimate from with function regression method. Similarly, we can define

\[ S_{U \times V \times U'} = \{(u, v, v')|(u, v, u', v') \in S\} \]  

(5)

\[ S_{U' \times V \times U'} = \{(u, u', v')|(u, v, u', v') \in S\} \]  

(6)

\[ S_{V \times U' \times V'} = \{(v, u', v')|(u, v, u', v') \in S\} \]  

(7)

and estimate \( v' = g_2(u, v), u = g_1(u', v') \) and \( v = g_2(u', v') \) from \( S_{U \times V \times U'}, S_{U \times U' \times V'} \) and \( S_{V \times U' \times V'} \) respectively with function regression method.

For convenience, we name the above technique as subspace projection.

3.2. RVM learning

In theory, correspondence function \( f \) can be estimated by regression method by subspace projection technique. In correspondence problem, however, putative correspondences are usually corrupted with noise and mismatches. The projection of mismatches are usually inconsistent with \( g_i \) and \( g'_i \), that is, the mismatches are outliers for them. And many of the outliers may have undue influence on the estimation of \( g_i \) and \( g'_i \), and they usually are called influentials in robust statistics.

Relevance Vector Machine (RVM) is a typical Bayesian method for estimation. The fundamentals of this method are Automatic Relevance Determination (ARD), Bayesian Hierarchical Prior model and kernel technique [18]. By the ARD principle, RVM can select out the relevant vectors for learning and prune out the redundant observations. By the Bayesian Hierarchical Prior model, the learning method RVM can obtained the property of Sparseness. Furthermore, our research shows that the regression method RVM is very robust against outliers. Therefore, we adopted the RVM and the above subspace projection technique in this work to estimate correspondence view.

4. Experiments

In this section, we study the performance of our proposed method by real image pairs.

There are two images of a relievo in Figure 1 a), and we want to establish point correspondences between them. The putative correspondences \( S \) in Figure 1 b) are computed from the SIFT keypoints by Nearest Neighbor method [9]. Due to local ambiguousness, there are many mismatches in \( S \). Therefore, the corresponding projection \( S_{U \times V \times U'}, S_{U \times V \times V'}, S_{U \times U' \times U'} \) and \( S_{V \times U' \times V'} \) are all contaminated with a larger percentage of outliers. We estimated \( u' = g_1(u, v), v' = g_2(u, v), u = g'_1(u', v') \) and \( v = g'_2(u', v') \) from them with RVM and reject the mismatches from \( S \) by checking consistency of the putative correspondences with the correspondence views, the consistent putative correspondences and the inconsistent ones are presented in Figure 1 c) and d) respectively. The experimental results show that RVM can be successfully used in correspondence view learning for mismatch rejecting.

5. Conclusion

Outlier rejecting is an important problem in computer vision. And correspondence view (CV) is a recently introduced concept for rejecting outliers. We studies CV learning and outliers rejecting for fish-eye camera images. Experiments on real image pairs demonstrate the feasibility and excellent performance of our proposed method. In future work, we will study this method on more extensively.

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References

Figure 1. Rejecting mismatches/outliers by CV. a) original image pair; b) putative correspondences with outliers; c) the identified correspondence points; e) the identified mismatches. (For visibility, only 50 randomly selected point pairs are presented in b), c), d)


