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A Fuzzy 3D Registration Method

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Abstract

An important problem in computer vision is to recover how features extrated from images are connected to either existing models. In this paper, we focus on solving the *registration* problem, i.e obtaining rigid displacement parameters between several 3D data, whether partial or exhaustive. We present a general method performing robust 3D location and fitting based on fuzzy clustering method handling noisy motions. We show results on syntetic and real 3D data.

1 Introduction

Model-based interpretation of 3D reconstruction algorithms outputs has received a growing attention in the recent years. Specifically, 3D data matching relative to a reference model, produced either interactively or automatically is of crucial importance. Recent examples can be found in topics as different as 3D medical imaging [2], aerial site observation [12], or range images for cartographic mapping [13].

We distinguish two major approaches for 3D registration: iterative approaches such "Iterative Closest Point" methods (ICP) [4, 23, 14] and combinatorial approaches [2, 19, 11] such hash table and generalized Hough transform. Iterative methods perform fine fitting only when initialisation step is near optimal solution. Hash table and generalized Hough transform technics are less robust because the result is very sensitive to noisy data as well as to the choice of the discretization steps in the accumulation space. In this paper, we propose a robust method for 3D data registration with object model that takes advantage of these two approaches (section 2). It proceeds in three steps. First, we look for the set of all possible rigid motions between data and model with a feature-to-feature correspondence algorithm. Rigid motions which closely register an object model to 3D data are swamped in a noise set of possible but not significant motions. To select the most relevant motion, a confidence factor, based on feature-to-feature correspondence, is introduced in order to cluster motions among noise in a fuzzy way. Thus, we propose an extension of the Dave's clustering method [9]. Finally, a local and accurate fitting is achieved between data and model. In section 3, we discuss the advantages of the proposed method and show results on synthetic and real 3D data.

2 General schema

2.1 3D feature matching

3D matching is obtained by a combinatorial approach. Robust 3D subsets are selected as features in the data as well as in the object model. We suppose that a technique to compute the possible rigid motions between any two subsets of a same type is available. By way of illustration, planar patches were used in this paper. Other geometric features can be used, such as 3D bases of 4 points [19], couples of segments, or local Frénet reference systems on curves [11].

Rigid motions produced by bad matches systematically swamp significant motions with noise. So, an important characteristic of the data is the ratio of the number of bad matches over the total number of correspondences. In the case where both 3D data set and object model are composed of n features, the ratio of bad match induced motions is $1 - \frac{1}{n}$: this ratio increases rapidly with n. Consequently, it is better to choose relatively abstract 3D features, like planar patches, to avoid combinatorial explosion.

One can estimate the similarity of the two matched features by computing characteristics that are invariant by rigid motion. It is then easy to construct a criterion based upon invariant properties of a feature. For planar patches, we have used the first and second singular values α and β of the inertia matrix as invariants. Then, we chose the a-priori criterion

$$f = \frac{1}{(1 + \frac{|\alpha_1 - \alpha_2|}{I})} \frac{1}{(1 + \frac{|\beta_1 - \beta_2|}{I})} \tag{1}$$

where I is the variance of the error observed on the localization of the 3D data. This criterion gives a confidence value between 0 and 1 for each match. The parameter I can be estimated and fixed off-line for any given computer vision algorithm. Thus, other additive informations, such as color, can also be integrated in the scheme by designing an adequate criterion.

2.2 Coarse 3D location

From the first step, we obtain a set of 3D rigid motions, each of which is related with a confidence weight f (equation (1)). A 3D rigid motion is represented by 3 angles and 3 terms of translation, therefore as a point in $\mathbb{R}^6$. In this set, a local accumulation point expresses a significant hypothesis of registration between a part of the data and a part of the object model. To select the accumulation centroids providing 3D object location in a robust way, a fuzzy clustering method will be used since it can handle several motion hypothesis at the same time.

2.2.1 Fuzzy approach

Fuzzy sets theory brings mathematical tools to handle uncertainty properties of computer vision data. Clustering technics are appropriate, in this case of study, to globally compute membership degrees in a robust way. The main idea is to allow distributed membership of a given pattern to several sub-sets in the feature space. Fuzzy C-Means clustering algorithms were, first, generalized by Bezdek (FCM) [5]. Several developpement and application were performed for image segmentation (range images [16, 15], medical imaging [6, 7, 3, 10], indoor sceen [8], texture [6]).

For 3D registration problems, we consider the set of possible motion as working space. In this case significant clusters are flooded by noisy data so that it is essential to model noise. Dave [9] have proposed an algorithm introduceing the concept of noise cluster. This additional cluster is designed to collect the noise data points. In particular, all the points in the data set are at the same distance from the noise prototype. To control this algorithm a new parameter λ is needed which specifies the ratio of noise points in the data set.

2.2.2 Algorithm

Dave's method gives excellent results when the ratio of noise points is not very important (ratio lower than 90% of noise points). In our problem, the noise point number n is too important (figure 1) so that noise cluster, without additionnal information, can not decide between significant and noisy data. To improve the efficiency of Dave's algorithm, we introduce the confidence weight f_i (equation (1) (express in terms of invariant rigid motion features) related to each $\mathbb{R}^6$ data point i in addition to its membership degree. The modified algorithm is summarized as follows:

step 1 : Fix the number of clusters c, and fix the exponent m. Compute the initial location of the cluster centers v_i by an FCM method for example. Specify the parameter λ linked to the noise ratio of the data set.

step 2 : Generate a new partition using the following equation of the fuzzy memberships:

$$u_{ik} = \frac{1}{\sum_{j=1}^{c} \left(\frac{d_{ik}}{d_{jk}}\right)^{\frac{2}{m-1}}}$$

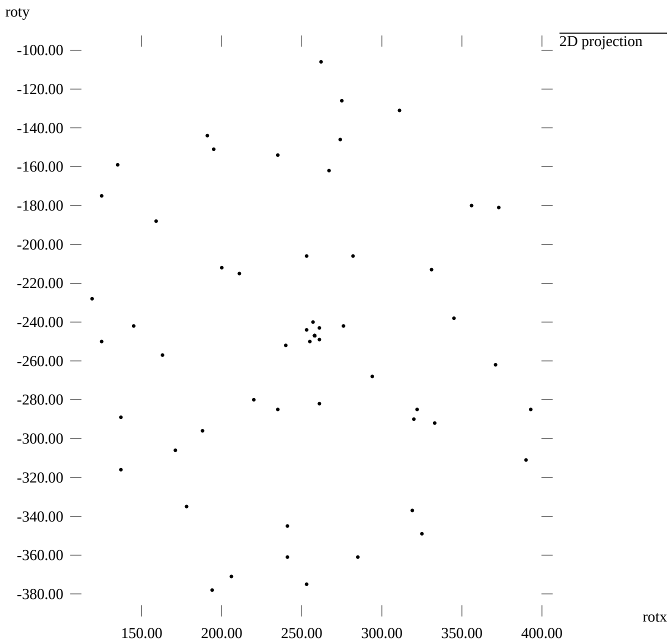

Figure 1: 2D projection of 3D rotation set. Central accumulation point corresponds to interesting registration hypothesis.

step 3 : Calculate new cluster centers using the following equation (for $i = 1$ to $c - 1$):

$$v_i = \frac{\sum_{k=1}^{n} f_k u_{ik}^m x_k}{\sum_{k=1}^{n} f_k u_{ik}^m}$$

step 4 : If the distance partition is stable, stop; else goto step 2.

x_i is an element of the data set of n points in $\mathbb{R}^p$ ($p = 6$ in our application) and its confidence weight is f_i. d_{ik} is defined as the euclidean distance between the data point x_k and the cluster prototype v_i for $i = 1$ to $c - 1$, and for the noise cluster as :

$$d_{ck}^2 = \frac{\lambda}{n(c-1)} \sum_{i=1}^{c-1} \sum_{l=1}^{n} d_{il}^2 \tag{2}$$

u_{ik} is the membership degre. The use of the f_i confidence weights is a natural and simple extension of fuzzy clustering methods allowing to preserve a ratio of noise points and more generally to manage additive knowledge on each point. The demonstration of the convergence of the extended algorithm offers no difficulty.

2.3 Fine fitting

The clustering method gives $c - 1$ different interesting hypotheses of rigid motion, such that a portion of the data model and of the object model are overlapped. It is often needed to improve 3D registration by local fitting. We use an iterative registration procedure based on explicit correspondences established between points of the data and the closest point of the reference object (ICP) [4]. This iterative method converges to a position where the distance between data and reference model is locally minimal. The ICP methods have, generally, a high computation cost, but in our approach, only a few iterations are necessary because the clustering method gives solutions very close to local minima. Consequently, an accurate 3D registration is obtained for each hypothesis. The mean distance between data and object models gives a criterion for hypothesis selection and sorting. Lower the mean distance is, better is the solution.

3 Results

This method was integrated into indoor scene interpretation system, based on stereoscopic images, performing camera calibration [22], region image segmentation [8, 1, 18], region matching for each couple of image [20, 17] and finally 3D reconstruction [21]. We have validate the presented approach on synthetic as well as real data. The number of clusters c is determined by an examination of the symmetry of the object model. The only critical parameter is the noise parameter λ (introduced in (2)).

3.1 Dealing with symmetries

An advantage of the proposed method is the given possibility to manage a set of possible coarse registrations. In particular, the number of clusters must be chosen by a analysis of the symmetries of the 3D object. For example in figure 3, the 3D object has planar symmetries, thus two symmetrical positions are possible for the global registration. This two registrations are obtained with $c = 3$, $m = 1.5$, $\lambda = 0.035$ and $I = 0.1$. Fine fitting result match exactly figure 3 (a) i.e. original 3D object.

	rot_x	rot_y	rot_z	$trans_x$	$trans_y$	$trans_z$
cluster 1	0.005	0.882	0.017	0.0173	-0.0023	0.0072
cluster 2	2.919	-0.012	0.854	0.0061	0.0165	-0.0166
true 1	0.000	1.000	0.000	0.0000	0.0000	0.0000
true 2	3.014	0.000	0.884	0.0000	0.0000	0.0000

Table 1: *Values of the two symmetrical rigid motions obtained by the classification algorithm in the coarse stage and the true values.*

3.2 Registration with several objects

(a) (b) (c)

Figure 2: (a)(b) Images of a real scene. Views of the 3D data obtained by stereovision algorithms on this images are shown in figure 4(a)(d). (c) Synthetic point of view of the registered models (see figure 4(c)(f)) on which the original image (a) is reprojected.

One advantage of the proposed method is its robustness, allowing to produce registrations with several objects. For example, on 3D data (figure 4(a)(d)) obtained with stereovision algorithms on real images (figure 2(a)(b)), models of a ball and of a planar object are registered and accurately fitted with the proposed method (figure 4). The relevance of the method is demonstrated in figure 2(c) showing a synthetic point of view of the registered models .

At last interesting hypothesis, obtained by clustering, are fitted accurately with all data informations and sorted in function of the quality of the data fusion. For example, in this real data with complexes objects, 6 clusters are obtained corresponding to 6 positions of the ball. One of the right registration (figure 4(e)) is the position where the residual distance is minimum. The used parameters in this experiments are $c = 7$, $m = 1.5$, $\lambda = 0.01$ and $I = 0.2$.

4 Conclusion

We proposed a new 3D registration method. Coarse 3D object location is first obtained. This method takes advantages of fuzzy clustering algorithms with noise data to produce robust results. Then, a fine and local fitting is performed to achieve accurate 3D registration. The method is easily controlled by two parameters: the number of clusters and the noise ratio. Interesting results for a geometric model-based interpretation are obtained, with a low cost of computation.

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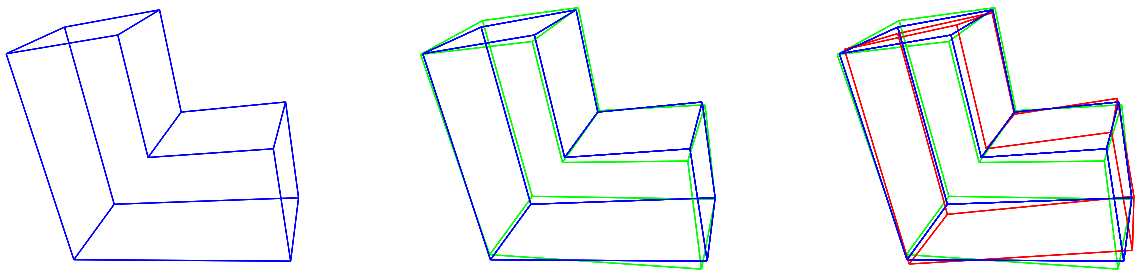
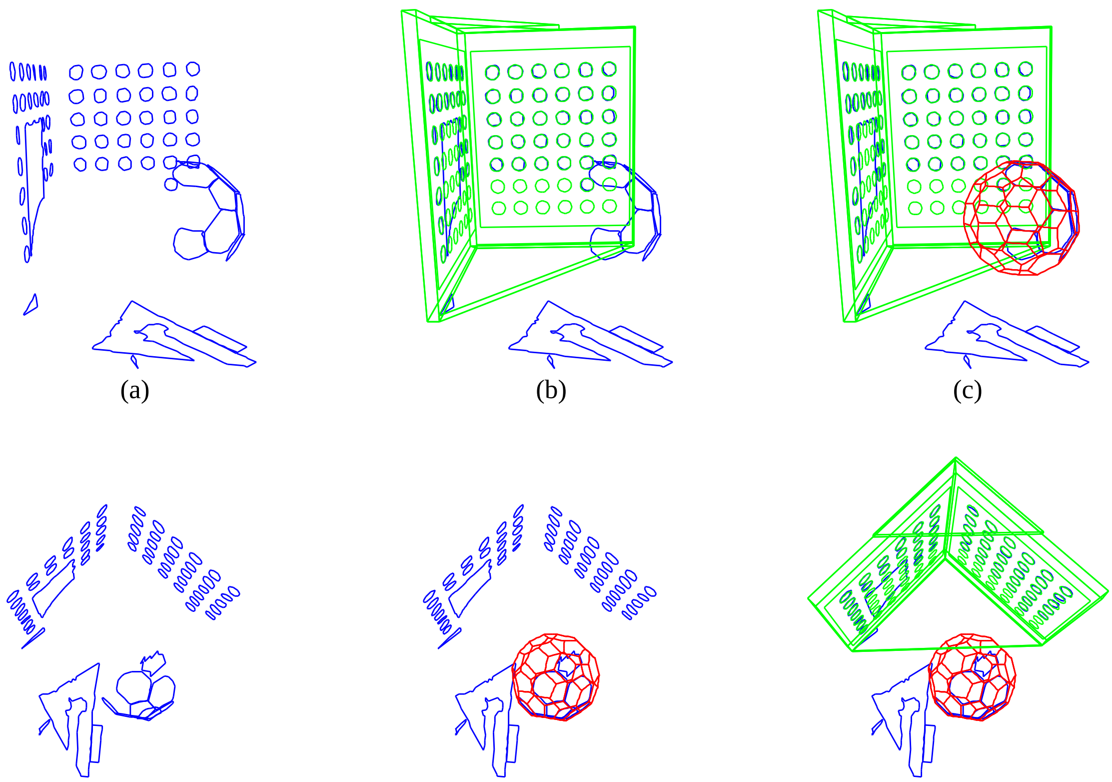


(a) (b) (c)

Figure 3: *(a) Synthetic 3D Data. (b) Approximated global registration given by one cluster and the two possible (because of the object symmetries) positions of the registered reference model (c).*



(a) (b) (c)

(d) (e) (f)

Figure 4: *(a) and (d) are two points of view of the reconstructed 3D data. In (b) the planar object is registered on 3D data. In (e) only the ball is registered, whereas (c) and (f) show the registration of both planar and 3D objects. Models are registered with the coarse method and a fitting algorithm is used to produce an accurate registration.*