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A Survey on Rigid Point-Sets Registration

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Abstract: Registration of two point-sets involves finding meaningful correspondences among points, or recovering the underlying spatial transformation. There already exist several different registration methods, which can be grouped into rigid registration and non-rigid registration. Rigid registration is considered be easy but quite necessary, compared to non-rigid registration. This paper summarizes rigid point-sets registration methods such as Iterative Closest Point (ICP), Principle Component Analysis (PCA) and Singular Value Decomposition (SVD), in where point-sets are the 2D or 3D coordinates usually of either a surface of an object, or the points occupied by the object. More specifically, this paper provides a comprehensive overview of rigid point-sets registration methods.

Keywords: Rigid registration; Point-set; Iterative closest point (ICP); Transformation; principal component analysis (PCA)

1. Introduction

Over the years, point-sets registration has played a crucial role in a wide range of image applications such as image segmentation [1], object detection [2,3], 3D image reconstruction [4,5], and image fusion [6-8], to name a few. Registration of point-sets involves finding meaningful correspondences among points, or recovering the underlying spatial transformation. There already exist several different registration methods for real-world applications, which can be grouped into rigid registration and non-rigid registration. For rigid registration, the underlying transformations are rigid and include rotation or translation. For non-rigid registration, the underlying transformations are non-rigid, such as affine or curved transformations. Compared with non-rigid registration, rigid registration is quite simple and easy to implement, and it also has wide applications in image processing especially medical image processing field. This paper summarizes and discusses prior research regarding registration methods.

Rigid transformation includes isotropic transformations that preserves the distances in Euclidean space. So, it is also called Euclidean transformation [9,10]. When an Euclidean transformation is considered, the linear mapping T consists of two parameter elements (R,t), wherein rotation matrix R is required to be an orthogonal matrix, and t is a translation vector. For this reason, rigid transformation is also categorized as linear transformation. Rigid transformation typically is modeled by six Degree Of Freedom (DOF) for 3D data or three DOF for 2D data. Regardless of the particular or generic registration methods employed, correspondences and transformations are the two key components of rigid point-sets registration algorithms. Existing rigid registration methods can thus be described according to the combination of these two components. Under the designed classification criteria of registration approaches, extensive summarization is extended based on several state-of-the-art registration methods.

The remainder of this paper is organized as follows: Section2 discusses rigid point-sets registration methods determining correspondences and transformations. Following that, the rigid point registration methods determining transformations such as PCA and SVD are presented in Section3. Section4 provides a summary to end the paper.

2. Rigid Registration Methods Determining Correspondences and Transformations

In this registration procedure, the correspondences and transformation parameters are unknown. The Expectation Maximization (EM) algorithm, which updates the correspondences and transformation parameters iteratively, is appropriate for deriving the closed-form solution.

2.1. Iterative closest point (ICP) registration algorithm

Iterative Closest Point (ICP) is a popular rigid point-sets registration method that has been applied successfully to a wide variety of registration problems [11,12]. ICP has become the generic framework of rigid point-sets registration for determining unknown correspondences and unknown Euclidean transformation. Given two point-sets $X=\{x_1,x_2,\ldots x_M\}$,and $Y=\{y_1,y_2,\ldots y_N\}$, where $x_j,y_i\in R^d$, the main idea of ICP is that for each point in set Y, the closest point in set X is searched to form a correspondence set. Based on set Y and the correspondence set, an orthogonal rotation matrix R and translation vector t are then updated iteratively until the terminal conditions are satisfied. The three basic steps of ICP are as follows:

Step1: Search a closest point x_j for $y_i \in Y$, then define a correspondence set as

$N_Y(X) = \{x_j \mid d(y_i, x_j) = \arg\min_{x \in X} d(y_i, x)\}$

Step2: Compute rotation matrix R^k and translation vector t^k using the Singular Value Decomposition (SVD) technique based on sets $N_Y(X)$ and Y ; and

Step3: Updates Y using transformation (R^k, t^k) and accumulates R and t as:

$$Y = R^k Y + t^k \quad (1)$$

$$R = R^k R \quad (2)$$

$$t = R^k t + t^k \quad (3)$$

To define the rotation R and translation t of a rigid transformation, a cost function must be derived according to the predefined Euclidean measurement:

$$J(R,t;X,Y) = \sum_{i=1}^{N} w_i \left\| x_{p(i)} - Ry_i - t \right\|^2$$
$$R^T R = I \quad (4)$$
$$\det(R) = 1$$

Permutation $p(i)$ of index i means that $x_{p(i)}$ is the nearest neighbor of y_i , and weight $w_i \in \{0,1\}$ is introduced to represent whether point y_i has correspondences or not. When y_i finds a nearest neighbor in X , weight w_i is set to 1, otherwise 0. The constraint conditions guarantee that rotation matrix R is an identical and orthogonal matrix.

In each iteration, correspondences can be computed using the nearest-neighbor scheme and transformation parameters can be determined by either SVD or quaternion technique [13]. Though effective, ICP is an expensive computational algorithm with $O(MN)$ because correspondences must be computed for each point of set X in each iteration. Furthermore, its convergence relies heavily on better initialization and tends toward the local minimum.

2.2. Variants ICP registration algorithms

In an effort to remedy disadvantages in the original ICP, later researchers attempted to reduce the computational cost of establishing correspondences. Obviously, the fewer the number of points to be registered, the faster the ICP registration works. A coarse-to-fine selection point scheme was used in Picky ICP to decrease the number of points to be registered [14]. Other researchers have adopted local search strategies to shrink the search space of the closest points such as the neighborhood search algorithm (see Figure1) [15,16] and $k-d$ tree nearest-neighbor search algorithm [16,17]. Utilizing a local instead of global search to obtain correspondence pairs may neglect some coherent information, however basically forming a tradeoff between computational complexity and registration accuracy.

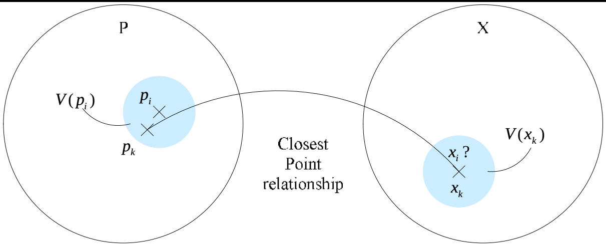

Figure 1. Neighborhood Search Scheme used by

Another relevant study employed a coarse-to-fine, multi-resolution scheme to improve registration accuracy, in which the coarser solution is improved successively by the next finer representation [16,18]. The number of hierarchical iterations essentially affects the computational complexity of the coarse-to-fine strategy. A comprehensive look-up matrix used was introduced to ICP to denote the CICP algorithm, which establishes correspondences [19]. In CICP, a line-by-line followed by a column-by-column method (instead of only line-by-line employed in Picky ICP) was used to search corresponding pairs. This method guarantees that the correspondences form a bijection, however, it may mistake good correspondence pairs for noisy data and mistakenly reject them.

In an effort to improve the convergence rate of ICP, a linear approximation and parabolic interpolant were used to accelerate the updating of registration parameters by [11]. Similarly, an extrapolation method was applied to transformation parameters to speed up the convergence of Picky ICP by [16]. Researchers highlighted the fact that the number of iterations of ICP has a polynomial relationship to the number of input points under the root mean squared (RMS) distance and one-sided Hausdorff distance [20]. Another study introduced a uniform sampling scheme to ICP for the normals on nearly-flat meshes to improve the convergence of range image registration [21]. To speed up the convergence of standard ICP registration, gradient-based optimization strategies such as nonlinear Levenberg-Marquardt have been utilized (called LM-ICP algorithm) to update transformation parameters by [22]. In addition, LM-ICP is tuned by a robust Huber kernel to improve robustness to noise and outliers. Any enhanced initialization of ICP variants implies that two required point-sets are closer at the time they begin to be registered. Evolutionary computation has been used to optimize the initial Euclidean transformation parameters by [23].

Branch-and-bound (BnB) searching, which minimizes the risk of trapping into local minima, is a method commonly used to search global solutions [24-26]. A notable example, the BnB global search algorithm, was proposed to determine rotation transformation and correspondences simultaneously by [27]. When correspondences are given, Euclidean or similarity transformation is computed via branch-and-bound algorithm to solve a global, non-convex optimization problem [24]. An innovative study proposed a globally optimal ICP, Go-ICP, with branch-and-bound (BnB) for 3D Euclidean registration where in subcubes of solution space, the rotation and translation provided by a nested BnB search algorithm provide the initialization of local ICP registration [26]. This method assists ICP to escape local minima (see Figure 2). The BnB search algorithm can afford accurate solutions with high computational cost and without convergence dependent on initialization. However, the domain of unknown transformation parameters is given in closed-form, which limits the transformations to Euclidean, similarity, and affine cases. It is worth mentioning that similarity transformations with isotropic scaling ($s \neq 1$) are an extension of Euclidean transformation and that similarity transformations with anisotropic scaling [28] are affine transformations.

It is necessary to consider the robustness of ICP-based algorithms to noise and outliers, because both are unavoidable during data collection. Researchers have used predefined distance thresholds to remove outlier candidates when points find their closest neighbors [11,14,16,19]. However, most of the related algorithms cannot guarantee convergence.

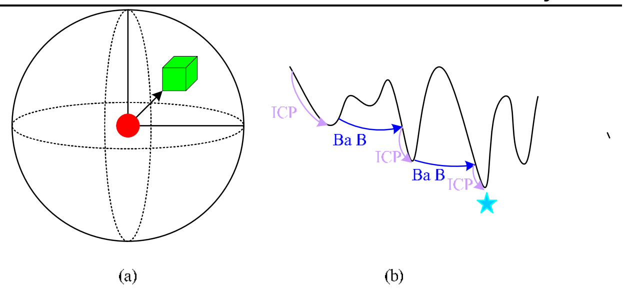

Figure 2. Go-ICP algorithm (a) Rotation transformations space SO(3) using p -ball. (b) Conduct BnB and ICP alternatively to jump out the local minima.

When the ratio of outliers is known, trimmed ICP can determine the optimal alignment; when the alignment is given, RANSAC-based methods or nonlinear estimator can be used to improve the robustness to noisy data [29]. A fractional ICP (FICP) based on a fractional root mean squared distance was presented in a relevant study to manage outliers by [30]. FICP can solve the outlier ratio and alignment simultaneously within an ICP iterative procedure. The Expectation Maximization (EM) algorithm combined with ICP, EM-ICP, has also been used to manage noisy and large data sets [31,32]. All considered aspects of the ICP variants are depicted in Figure 3.

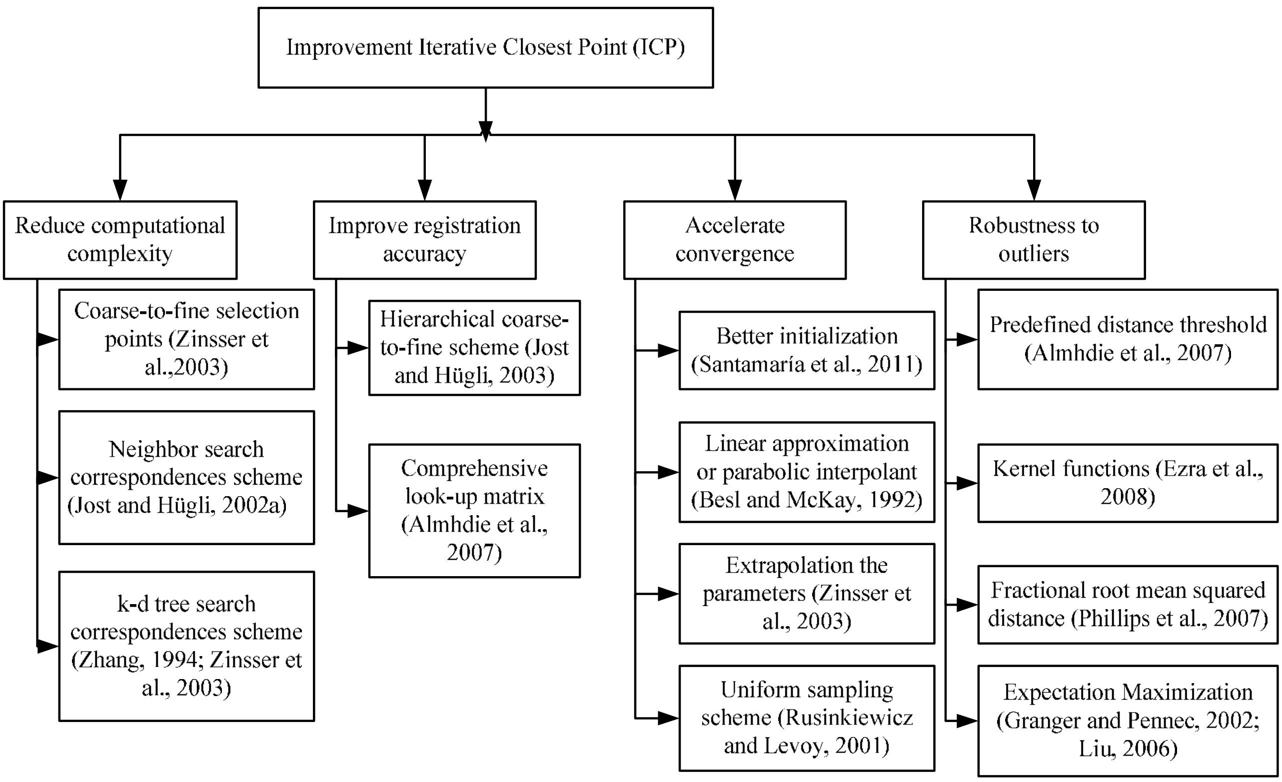

Figure3. An Overview of Existing Techniques used to Improve Performance in ICP

Note that an exhaustive and comparative summary of ICP variants has been presented as far as the effect on the speed [21]. The various improved versions of the ICP registration on 3D symmetry plane localization were again discussed by [33]. Additionally, rigid 3D point cloud registration methods including PCA, SVD and ICP were reviewed and analyzed by [34]. In another relevant survey article, qualitative review on 3D rigid coarse matching was presented to offer a standard formal notation of the existing methods by [35]. Another notable registration survey considered both 3D point clouds and meshes within the scope of surface registration, which comprehensively covers different aspects of either rigid or non-rigid registration [36].

3. Rigid Registration Methods Determining Transformations

The standard ICP algorithm has become a generic point registration template that iteratively updates correspondences and transformations until convergence. ICP and its variants have been researched extensively and shown favourable performance overall as applied to a variety of registration scenarios [11,16,26,32,33]. An alternative strategy for rigid transformations without (or without explicitly) considering correspondences is required in some situations, however, especially during the preprocessing stage. For instance, the images to be aligned may originate from different resources, such as a set partially collected from a web camera and partially from a DSLR (digital single-lens reflex) camera [37]. Situations such as these require rigid alignment schemes like the three discussed below, Principal Component Analysis (PCA), Singular Value Decomposition (SVD), and neural networks (NN), to determine the unknown transformation parameters.

3.1. Principle component analysis (PCA)-based alignment methods

The canonical coordinate system is a novel type of coordinate system that spans orthogonal axes which are extracted from a covariance matrix of the point-sets to be aligned [38,39]. In general, there are three (for 2D data) or six (for 3D data) unknown parameters to be determined comprised of origin location (x_0, y_0, z_0) and orientation angles (q_x, q_y, q_z) [34,39]; all images are transformed into the coordinate system to align them.

Principal Component Analysis (PCA) is often utilized as a dimensionality reduction method to remove the linear correlation between variables (features). The method yields an orthogonal transformation (i.e., a matrix of the eigenvectors) by means of Singular Value Decomposition (SVD) technique [40]. PCA maps the original data into a feature subspace that spans the set of orthogonal eigenvectors. Thus, the method can be used to perform global, rigid alignment without correspondences [34]. For source point cloud $X_{d\times N}$ and target point cloud $Y_{d\times M}$, the respective centroids C_X and C_Y are computed while the respective principal directions are extracted from the normalized clouds denoted V_X and V_Y (V_X and V_Y are an orthogonal matrix, and each column of V_X or V_Y is an eigenvector). The alignment of X and Y is then converted into the alignment of two coordinate systems (C_X, V_X) and (C_Y, V_Y) (Figure4). The solution is derived as rotation matrix $R = V_Y V_X'$ and translation $t = C_Y - RC_X$.

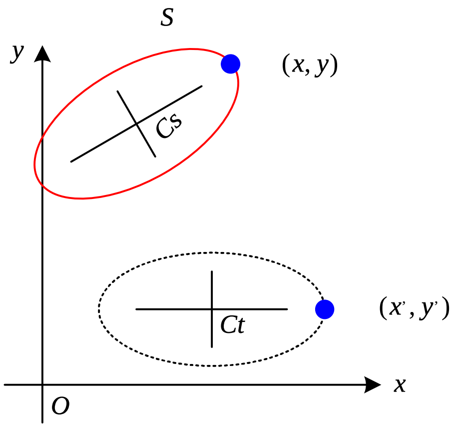

Figure 4. Alignment between two Point-sets based on PCA Method

As is commonly known, nonlinear problems can be reduced to linear problems using kernel techniques. Point-sets registration in a 3D Euclidean space can be converted into a rigid registration based on the kernel PCA method in a high-dimensional feature space [41]. The primary goal of this method is to determine the inverse transformation mapped from Hilbert space to 3D Euclidean space. PCA rigid alignment was utilized in another study to establish a domain adaptation algorithm that removes the discrepancy between source and target domains that have been generated from different marginal distributions [37]. This method reduces computational cost by allowing the intermediate manifold space to be neglected. In another study, scale alignment between two point-sets was successfully converted into the determining scale factor of two sets of cumulative contribution rate curves, defined by the PCA eigenvalues of spin images of 3D point-sets [42].

A cascade Principal Component Analysis (PCA) model was explored in another study for normalizing the pose of raw-source face images to be frontal. The normalized source model is then registered to the standard feature model using the ICP algorithm by [43]. This model is simple and easy to implement however it is sensitive to occlusion, non-symmetry, and non-facial data. Another coarse-to-fine method proposed to locate the symmetry plane of 3D faces is performed using PCA techniques accompanied by the ICP algorithm [44], where PCA initializes the symmetry plane before all 3D faces are projected to obtain mirrored data based on the coarse symmetry plane (called the "mirror plane"). The ICP method accommodates the precise correspondences between the original 3D face data and the mirrored data, then the symmetry plane is updated using the fitting plane from the established correspondences. To improve the accuracy of the initial symmetry plane obtained by PCA, the initial symmetry plane is refined according to nose tip and nose bridge information [45,46]. To automatically align multiple images while connecting the image alignment and image representation, a transform-invariant PCA (TIPCA) method was developed for 2D image recognition [47]. Under circumstances in which pixel intensity value is replaced with pixel coordinates $I(v)$, where $v=[x, y]^T$, i.e., each 2D image can be viewed as a 2D point cloud, TIPCA then iteratively solves the alignment of multiple images and the optimal eigenspace by minimizing the objective function. The TIPCA alignment method benefits invariant descriptors and classification methods.

In essence, PCA-based alignment is a statistical method of deriving orthogonal rotation and translation transformation. It is easy to implement and has relatively low computational cost, however, it is sensitive to noise and outliers. In addition, it is not sufficiently reliable for circular or symmetrical shapes.

3.2. Singular value decomposition (SVD)-based alignment methods

Singular Value Decomposition (SVD) is another statistical method for identifying an orthogonal rotation matrix and translation for corresponding points. There are significant differences between SVD and PCA. Given two point-sets $P=\{p_1,p_2,\mathbf{L},p_n\}$ with centroid C_p and $Q=\{q_1,q_2,\mathbf{L},q_n\}$ with centroid C_q, where column vectors p_i and q_i are a pair of corresponding points, the key steps of SVD alignment are as follows:

Step 1: Construct two matrices $P=[p_1',p_2',\mathbf{L},p_n']$ and $Q=[q_1',q_2',\mathbf{L},q_n']$ where $p_i'=p_i-C_p$ and $q_i'=q_i-C_q$, $i=1,2,\mathbf{L},n$.

Step 2: Compute covariance matrix $C=PQ^T$.

Step 3: Find the optimal rotation matrix R by minimizing the sum of the pairwise distances $\sum_{i=1}^{n}\|p_i'-q_i'\|^2$ as equivalent to maximize the trace of matrix RC.

Step 4: SVD of C is $[U,A,V^T]=svd(C)$.

Step 5: Define orthogonal rotation matrix $R=UV^T$.

Compared to PCA, precise correspondences-based SVD is insensitive to noise and outliers and altogether more stable for circular or symmetrical shapes. Basically, SVD relies heavily on correct correspondences.

Neural network-based registration methods are also valuable, though they show limited applicability for point-sets registration. In some notable studies, researchers employed a feed-forward neural network to conduct rigid registration, where the outputs were the transformation parameters to be estimated (or the points of target) [48-51]. However, maintaining the orthogonality of Euclidean transformation as well as the high complexity of training neural network limit its application in point-sets registration.

The basic natures and limitations of the three types of rigid alignment methods discussed above are listed in Table 1.

Table 1. Comparison among PCA-based, SVD-based and NN-based alignment methods

Schemes	Advantages	Limitations
PCA-based	Easy to implement; Unsupervised data analysis for two point-sets	Sensitive to noise and outliers, unstable to a circular or symmetrical shape
SVD-based	Sound mathematical background; Unsupervised data analysis for two corresponding point-sets	Heavily rely on accurate correspondences
NN-based	Flexible architecture; Supervised learning for two point-sets	Black-box learning process and maintain orthogonal rotation

4 . Conclusions

ICP iteratively uses nearest neighbors as correspondences and determines orthogonal rotation matrix and translation vector from the covariance matrix before recovering the transformation. ICP has become a generic framework of rigid registration, and several variants were presented to overcome the limitations of original ICP. On the other hand, two point-sets are aligned without precise correspondences through SVD-based techniques. This paper summarized the state-of-the-art rigid registration methods according to two core components of registration to offer a comprehensive overview of rigid point-sets registration methods.

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