Automatic Image Registration Using Improved LBG Algorithm

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Abstract

Image registration is the process of transforming different sets of data into one coordinate system. This paper proposed automatic image registration using improved LBG algorithm. LBG Algorithm used k-means to refine these prototypes, this paper proposed improved k-means algorithm to enhance LBG algorithm. Experimental result shows that the proposed image registration method can improve the precise of image registration, is effective.

Keywords: Image Registration, Improved LBG Algorithm, Improved K-means Algorithm

1. Introduction

Image registration is the process of transforming different sets of data into one coordinate system. Data may be multiple photographs, data from different sensors, from different times, or from different viewpoints. It is used in computer vision, medical imaging, military automatic target recognition, and compiling and analyzing images and data from satellites. Registration is necessary in order to be able to compare or integrate the data obtained from these different measurements. Due to the diversity of images to be registered and due to various types of degradations it is impossible to design a universal method applicable to all registration tasks. Every method should take into account not only the assumed type of images but also noise corruption, required registration accuracy and application-dependent data characteristics.

Image registration or image alignment algorithms can be classified into intensity-based and feature-based. One of the images is referred to as the reference or source and the second image is referred to as the target or sensed. Image registration involves spatially transforming the target image to align with the reference image. Intensity-based methods compare intensity patterns in images via correlation metrics, while feature-based methods find correspondence between image features such as points, lines, and contours. Intensity-based methods register entire images or sub-images. If sub-images are registered, centers of corresponding sub-images are treated as corresponding feature points. Feature-based method established correspondence between a number of points in images. Knowing the correspondence between a number of points in images, a transformation is then determined to map the target image to the reference images, thereby establishing point-by-point correspondence between the reference and target images [1].

Image registration algorithms can also be classified according to the transformation models they use to relate the target image space to the reference image space. The first broad category of transformation models includes linear transformations, which include translation, rotation, scaling, and other affine transforms. Linear transformations are global in nature, thus, they cannot model local geometric differences between images. The second category of transformation models are elastic or non-rigid transformations. These transformations are capable of locally warping the target image to align with the reference image.

Felix Calderon et al. [2] presented a method to perform parametric image registration based on differential evolution. Besides using Differential Evolution, they proposed to use an error function robust enough to discard misleading information contained in outliers.

Fangfang Han et al. [3] proposed a preprocessing algorithm of medical image registration for PET and CT images. The algorithm process includes image normalization, CT image adaptive threshold adjustment and automatic extraction of tissues based on morphology, edge detection and statistical analysis theory, and improved PET image interpolation based on physical spacing of pixels.

Arun K.S. et al. [4] proposed a new feature based automatic registration algorithm based on robust
scale invariant feature transform (SIFT) features and Moving Least Squares (MLS). First, a robust SIFT algorithm is developed to find rotation and scale invariant features from the input images. Corresponding feature points are then matched using evidence accumulation. Finally the transformation parameters are estimated using Moving Least Squares (MLS) transformation.

Shu-Kai S. Fan et al. [5] proposed an image registration method that applies the information theorem to the corresponding intensity data. An entropy-based objective function is designed upon the histogram of the intensity differences. Intensity differences represent the differences of the corresponding pixels between the referenced and sensed images on the overlapping region. The sensed image is aligned to the referenced image by minimizing the entropy of the intensity differences through iteratively updating the parameters of the similarity transformation in the optimization process.

Jong-Min Kim et al. [6] studied about the real-time CCTV combined system using the local partial image and to suggest the combination and recognition method for frames. Its purpose is to reduce the combination speed of the suggested algorithm compared to the existing one and to enhance the overall recognition rate according to this. Since the existing SIFT algorithm method has a patent and a slow processing speed, they proposed the improved local image regenerating method, and the speed was raised according to the actual CCTV processing speed.

Jie Wang et al. [7] presented a non-rigid registration method for the restoration of double-sided historical manuscripts. Firstly, the gradient direction maps of the two images of a manuscript are examined to identify candidate control points. Then the correspondences of these points are established by minimizing a dissimilarity measure consisting of intensity, gradient and displacement. To fully capture the spatial relationship between the two images, a mapping function is defined as the combination of a global affine and local b-splines transformation. The cost function for optimization consists of two parts: normalized mutual information for the goal of similarity and space integral of the square of the second order derivatives for smoothness.

Hua Li et al. [8] presented an algorithm using point feature and intensity feature combined with the artificial immune algorithm (AI). First, the feature points of the two images are extracted by Harris corner detector to reduce the amount of computation. Then, the mutual information (MI) is used to be the similarity measure for MI algorithm based on intensity has excellent robustness and accuracy. Finally, the transformation parameters are calculated by Artificial Immune algorithm.

Youfu Wu et al. [9] first printout Gaussian-Hermite moments, and proposed a new method to extract the object’s features based on Gaussian-Hermite moments. Following, for training ART neural network, the moment features were inputted to ART as its parameters; so that, a classifier was realized for recognizing the moving objects.

Zezhong Xu et al. [10] proposed multi-view registration method. The proposed multi-view image registration method can handle the uncertainty efficiently. Multi-view image registration is to compute the globally consistent transformations of a sequence of images. Due to various uncertainties, multi-view image registration is considered as stochastic estimation problem. In order to improve global consistency of registration, the states of all viewpoints are estimated in a common state vector and covariance matrix. The system state consists of the position and orientation of viewpoints. System augmentation model is based on the coarsely pairwise matching. System observation model is constructed with feature correspondence. The position and orientation of viewpoints are augmented and estimated recursively with augmented Kalman filter. The global transformation of image is computed based on the estimated position and orientation of corresponding viewpoint.

The majority of the registration methods consist of the following four steps [11]: feature detection, feature matching, transform model estimation and image transformation. In the period of feature detection, salient and distinctive objects are manually or, automatically detected. For further processing, these features can be represented by their point representatives, which are called control points in the literature. In the period of feature matching, the correspondence between the features detected in the sensed image and those detected in the reference image is established. Various feature descriptors and similarity measures along with spatial relationships among the features are used for that purpose. In the period of transform model estimation, the type and parameters of the so-called mapping functions, aligning the sensed image with the reference image, are estimated. In the period of image transformation, the sensed image is transformed by means of the mapping functions. The implementation of each registration step has its typical problems. First, we have to decide what kind of feature is appropriate for
the given task. The features should be distinctive objects, which are frequently spread over the images and which are easily detectable. Usually, the physical interpretability of the features is demanded. The detected feature sets in the reference and sensed images must have enough common elements, even in situations when the images do not cover exactly the same scene or when there are object occlusions or other unexpected changes. The detection methods should have good localization accuracy and should not be sensitive to the assumed image degradation. In an ideal case, the algorithm should be able to detect the same features in all projections of the scenes regardless of the particular image deformation.

In the feature matching step, problems caused by non-correct feature detection or by image degradations can arise. Physically corresponding features can be dissimilar due to the different imaging conditions or due to the different spectral sensitivity of the sensors. The feature descriptors should be invariant to the assumed degradations. Simultaneously, they have to be enough to be able to distinguish among different features as well as sufficiently stable so as not to be influenced by slight unexpected feature variations and noise. The matching algorithm in the space of invariants should be robust and efficient. The algorithm must be able to work on the tensor with massive missing values even when no missing value appears in individual training samples.

Linde, Buzo and Gray (LBG) proposed a Vector Quantization design algorithm based on a training sequence. This paper proposed automatic image registration using improved LBG algorithm. LBG Algorithm used k-means to refine these prototypes, this paper proposed improved k-means algorithm to enhance LBG algorithm. Affine transform was used to construct the mapping function.

The rest of the paper is organized as follows. Section 2 is the description of improved LBG algorithm. Section 3 focuses on experiments and evaluations. Finally, we end this paper with a conclusion and the future work.

2. Improved LBG Algorithm

The module of improved LBG algorithm is the kernel of our method. The Linde Buzo Gray (LBG) algorithm [12] is a vector quantization algorithm to derive a good codebook. It is similar to the k-means method in data clustering. The use of a training sequence bypasses the need for multi-dimensional integration. The LBG algorithm is of iterative type. In each iteration step, a large set of vectors, generally referred to as training set, are needed to be processed. Every iteration, every vector is split into two new vectors.

Step 1. First, you find the sample mean or what we call the centroid \( z_1 \) for the entire data set. This is like if we were to have only one prototype. The sample mean is proven to minimize the total within class distance (total mean square distortion) for a single prototype.

Step 2. Set \( k = 1 \), \( x = 1 \). \( x \) is the index for the iteration. \( k \) counts the number of prototypes that have been generated. After the first step, we’ve only generated one prototype.

Step 3. If \( k < M \) (\( M \) being the target number of centroids that we’re trying to get), split the current centroids by adding small offsets. Let’s see how this is done.

Since we already have \( k \) prototypes, we need \( M - k \) additional prototypes. If \( M - k \geq k \), split all the existing centroids that have been created so far; otherwise, we split only \( M - k \) of them. We will denote the number of centroids which are split by \( m = \min(k, M - k) \), where \( m \) is the smaller of the two values.

For example, to split \( z_1^{(1)} \) into two centroids, let \( z_1^{(2)} = z_1^{(1)} \), \( z_2^{(2)} = z_1^{(1)} + \varepsilon \), where \( \varepsilon \) is a small offset and has a small norm and a random direction.

Step 4. \( k \leftarrow k + n \); \( x \leftarrow x + 1 \). The splitting has taken place.

Step 5. Use \( \{z_1^{(1)}, z_2^{(1)}, \ldots, z_n^{(1)}\} \) as initial prototypes, which includes the previously generated centroids and the newly split centroids. Apply k-means to refine these prototypes.

Step 6. Check whether the number of prototypes has reached the target number of prototypes. In other words, if \( k < M \), go back to step 3; otherwise, stop.

In the Step 5, it uses k-means to refine these prototypes. K-means clustering is a method of cluster analysis which aims to partition \( n \) observations into \( k \) clusters in which each observation belongs to the cluster with the nearest mean.

The steps of k-means clustering are given as follows.

1. Choose the number of clusters, \( k \).
2. Randomly generate \( k \) clusters and determine the cluster centers, or directly generate \( k \) random
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points as cluster centers.
3. Assign each point to the nearest cluster center.
4. Compute the new cluster centers.
5. Repeat the two previous step until some convergence criterion is met or the assignment has not changed.

We proposed the improved k-means algorithm, in order to improve LBG algorithm.

Define \( Y_m = \{y_{m,1}, y_{m,2}, \ldots, y_{m,M}\} \), for \( m=1, \ldots, M \).

Calculate \( k \) using formula:

\[
\hat{c} = \left[ \sum_{i=1}^{n} d_i / c \right] ;
\]

Initialization: since the initial cluster centroid can have a significant effect on the efficient, it pays to be more careful. In order to avoid picking too many cluster centroids that are close to one another. One way to overcome it is to start with picking a random vector as the first centroid, and then pick the vector that is least similar to it as the second centroid. Subsequent centroid is chosen such that they are farthest away from centroids that are already picked.

while not converged
    for each \( y_i \)
        while \( y_i \) is not assigned
            Calculate the Euclidean distance measure to each of the k clusters;
            Assign \( y_i \) to the nearest centroid;
            Group all unassigned as \( G \) with \( m \) as their nearest centroid;
            Calculate the priority value for: \( y_i \in G \);
            Assign \( y_i \in G \) to their nearest centroid based on the priority value;
            if \( y_i \) is not assigned then choose the next nearest centroid;
        end if
    end while
end for
Calculate the new centroid;
end while
If the required number of kernels \( M \) has been reached, or if all vectors have population less than the threshold \( \lambda \), then stop.

The detected features in the reference and sensed images can be matched by means of the image intensity values in their close neighborhoods, the feature spatial distribution, or the feature symbolic description.

The missing values are reconstructed by those available values sharing some factor values in the multi linear way. Technically speaking, a missing value can be reconstructed as long as there is one available value sharing one factor with it. This means the algorithm can work even when the majority is missing values.

We used affine transform to construct the mapping functions:

\[
u = a_0 + a_1 \cdot x + a_2 \cdot y
\]
\[
v = b_0 + b_1 \cdot x + b_2 \cdot y
\]

It can be used for multi-view registration assuming the distance of the camera to the scene is large in comparison to the size of the scanned area.

For a particular problem, only the coefficient vector accounting for the target factor is used (to find out the state of the target factor for the input image). Thus the influence of interferential factors can be filtered out. The mapping function constructed during the previous step is used to transform the sensed image and thus to register the images.
3. Experiments and evaluations

The accuracy evaluation of image registration is a nontrivial problem, partially because the errors can be dragged into the registration process in each of its stages and partially because it is hard to distinguish between registration inaccuracies and actual physical differences in the image contents. In this Section, we review basic error classes and methods for measuring the registration accuracy. Alignment error denotes the difference between the mapping model used for the registration and the actual between-image geometric distortion. Localization error denotes displacement of the control point coordinates due to their inaccurate detection. Matching error is measured by the number of false matches when establishing the correspondence between control point candidates. It is a serious mistake which usually leads to failure of the registration process and should be avoided.

We used 100000 images to experiment, including 10 clusters, every cluster included 10000 images. We compared the evaluate results of our ILBG (Improved LBG) algorithm with the results of LBG algorithm. Localization error, matching error, alignment error were used to evaluate our result. The evaluate result of LBG algorithm as Table 1 shows, the evaluate result of ILBG algorithm as Table 2 shows:

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<th>Table 1. The evaluate result of LBG algorithm</th>
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<td>localization error</td>
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The data in table 1 and table 2 shows, improved LBG algorithm can reduce the error of image registration, and improve the precise of image registration.

Figure 1, Figure 2 and Figure 3 denote localization error, matching error, alignment error on 10 clusters.
Experimental result shows that improved LBG algorithm can reduce the error of image registration, and improve the precise of image registration. The proposed ILBG algorithm of image registration is effective.

4. Conclusions and future work

Image similarities are broadly used in medical imaging. An image similarity measure quantifies the degree of similarity between intensity patterns in two images. The choice of an image similarity measure depends on the modality of the images to be registered. Common examples of image similarity measures include cross-correlation, mutual information, sum of squared intensity differences, and ratio image uniformity. This paper proposed automatic image registration using improved LBG algorithm. LBG Algorithm used k-means to refine these prototypes, this paper proposed improved k-means algorithm to enhance LBG algorithm. Affine transform was used to construct the mapping function. Experimental result shows that the proposed image registration method can improve the precise of image registration, and reduce error.

Also, there is a lot of room for improvement. For example, we need to speed up clustering algorithm in future. Many features can be used to match image, we need to find the appropriate features fit different condition.
5. References