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An adaptive image registration method based on SIFT features and RANSAC transform☆

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ABSTRACT

Scale Invariant Feature Transform (SIFT) is one of the most applicable algorithms used in the image registration problem for extracting and matching features. One of the efficient methods in reducing mismatches in this algorithm is the RANdom Sample Consensus (RANSAC) method. Besides the applicability of RANSAC, its threshold value is fixed, and it is empirically chosen. In this paper, a mean-based adaptive RANSAC is proposed at first. In this method, the threshold value of RANSAC is chosen based on the mean of distances between each point and it's model-transformed one. To increase the capability of the method, the second adaptive RANSAC method is proposed, which exploits the variance of the distances in addition to the mean value. Simulation results confirm the superiority of the proposed methods in comparison with classic ones in terms of True Positive rate, mismatches ratio, total number of matching, and two newly proposed evaluation criteria.

1. Introduction

IMAGE REGISTRATION is one of the most important fields in image processing, which has many applications such as in change detection [1], image fusion [2], image mosaic [3] and so on. Image registration is the mechanism of aligning two images from the same scene taken under different imaging conditions (different times, various angles, and different sensors) and this process aligns the reference and sensed images geometrically. Due to the different nature of the images, a unique method cannot be used for registration of all kinds of images. Accordingly, image registration techniques could be classified into two categories of feature [4] and area-based methods [5]. Generally, area-based methods are used when there are no important details and distinctive information, but feature-based methods are usually used when the local structure information of the image is more important than the intensity data [6].

Although there are various methods for feature-based registration, a majority of them are composed of the four steps including feature detection, feature matching, transform model estimation and image resampling [7]. Each of the mentioned registration steps plays an important role in the registration process. However, among them one of the important steps is the feature matching step. Scale Invariant Feature Transform (SIFT) algorithm is one of the most important detection and matching methods that is invariant against scale change and rotation [8]. Moreover, SIFT is stable against changes of illumination, affine distortion and noise [8]. These benefits make this algorithm very applicable in the process of image registration [9]. Despite the mentioned advantages, due to the lack of use of geometric information in the process of features

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matching, the SIFT algorithm has limitations such as the existence of a large number of mismatches that greatly affect the process of registration.

Generally, two different sets including the feature-descriptor, and spatial-relationship based methods are used to eliminate the mismatches, and increase the capability of SIFT. In feature descriptor method, a descriptor is created using the specifications of the area around each feature. Afterwards, the matches which their distance is more than a user-defined threshold value are considered as mismatches, and removed. Matching based on the nearest neighbor distance ratio [8], and dual matching [10] are examples of this matching type. Descriptors-based methods are easily implemented. However, when there are similar patterns or fewer texture details in the image, it leads to distinctiveness of descriptors, and may result in failures in the matching process. Spatial relationships methods use a geometric (transformation) model among features. After estimation of the model parameters, the mismatches are removed based on the distance between the features and the spatial information. This method is used when the detected features are ambiguous, or their neighbors are locally distorted [6], and it is greatly influenced by the ability of feature extraction algorithm. Examples of the methods that use spatial relationships are Graph Transformation Matching (GTM) [11], and RANdom Sample Consensus (RANSAC) algorithm [12].

GTM was originally introduced by Wendy [11]. GTM is an iterative algorithm and uses spatial relationships of the matching points. The algorithm is used in the mismatches elimination [13], image registration process [14], matching medical images [15], and face recognition [16]. However, this algorithm has some disadvantages. The GTM algorithm is based on the assumption that when the created graphs in the two images are aligned, all the matches will certainly be correct in the two images [14]. However, this assumption is not always true. Distortions such as scale differences and rotations created by the movement of the camera may cause the neighbors of two correct matching points not to be placed at the similar distances from the images. This may cause the graph of the two images not to be the same. To overcome these disadvantages, other algorithms such as RANSAC can be used.

RANSAC is a robust estimation method introduced by Fischler [12]. This algorithm offers a method for separating the subset of the matches and mismatches among initial matchings. It uses the removal of mismatches and estimation of the parameters of the model transformation. This algorithm is used to remove mismatches, and it is resistant and stable against noise. However, this algorithm also has some disadvantages. When the correct matches are fewer than 50%, the method is not very applicable. It is suitable only for linear systems. RANSAC cannot be repeated because it is based on random samples [17], and the implementation of this algorithm is time-consuming. To overcome some of the mentioned deficiencies, some methods are proposed in the literature [18-22]. In [18], using topological information, the matches are modified, and then RANSAN is applied to them. This approach can obtain better accuracy than RANSAC in fewer number of iterations. In [19], the feature points that are not related to the target area (image includes object and the background, and the target area is the object that we want to match) and crossing points are removed at first; then RANSAC is used to remove mismatches. In [20], an energy function model is used to measure the similarity of feature points before RANSAC algorithm in the Synthetic Aperture Radar (SAR) images, which may have speckle noise. Using this energy function improves the performance of the algorithm against mismatches. Reference [21] suggested a nonlinear RANSAC, as this algorithm is suitable for nonlinear systems. In reference [22], fast RANSAC method is suggested, which is improved regarding time and accuracy compared to RANSAC.

Another important disadvantage of RANSAC is that the number of correct matches depends on the threshold value. Although some works have been done about other disadvantages of RANSAC, research on calculation of the optimum threshold value is missing, and in most of the papers, this value is chosen experimentally. For example in [11] that is 0.001; in [23], 1; and in [24], 50. In reference [25], based on the required number of matches for the next processes, the threshold value is also manually selected.

Determination of the appropriate threshold value is very important in RANSAC. If a small value is selected, it leads to the removal of a large number of matches as mismatches, and thus reduces the rate of correct matches, and number of matches. Moreover, if a large value is selected for the threshold, it increases the rate of mismatches, and increases alignment error, which ultimately results in a serious impact on the registration process. On the other hand, optimum determination of the threshold value manually and experimentally is very difficult because it depends on the image type, distortion in the image, and image features. Due to the importance of determining the optimum threshold value in the RANSAC algorithm, proposing an adaptive RANSAC algorithm can be very applicable in image matching and registration applications.

In this paper, two adaptive approaches are proposed for image registration. In the first proposed method, the threshold value in RANSAC is selected based on the average distance between the transformation model and the matching points. To increase the efficiency of the first method in the case of similar patterns in the images and texture images, the second method is proposed. In the second method, for determining the adaptive threshold value, correct matches, and mismatches are considered as a classification problem. To do this, the variance between correct matches and mismatches classes is maximized. Another innovation of this paper is offering new criteria to evaluate the effectiveness of the matching methods. Classical criteria including false matching ratio and matches correctness cannot properly compare the performance of mismatch removal because these criteria do not consider the total number of matches. To overcome this problem, two new evaluation criteria of matches are proposed based on false matching ratio, correct matching ratio, and the total number of matches. The proposed criteria can be used in all feature-based matching algorithms effectively.

The organization of the rest of paper is as follows. In Section II, the basic RANSAC algorithm is described. In Section III, the proposed adaptive image registration methods are described. In Section IV, the simulation results are provided, and finally, the paper is concluded in Section V.