Image Registration based on SIFT Features and Adaptive RANSAC Transform

Zahra Hossein-nejad, Mehdi Nasri

Abstract—**Scale invariant feature transform (SIFT) is one of the most applicable algorithms used in the image registration problem for extracting and matching of the 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 new method is proposed where the threshold value is calculated based on the variance between the correct matches' and of mismatches classes. Simulation results confirm the superiority of the chosen threshold in different situations in comparison with classic RANSAC algorithms in terms of CMR and FMR**.

***Index Terms*—Image registration, SIFT features, RANSAC transform.**

I. INTRODUCTION

IMAGE REGISTRATION is one of the most important fields in image processing that has applications 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 different nature of images, a unique method cannot be used for registration 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].

Scale-invariant feature transform (SIFT) algorithm is one of the important methods to find features in the image that is invariant against scale change and rotation. Moreover, SIFT is stable against changes of illumination and affine distortion and noise [7]. These benefits make this algorithm very applicable in the process of image registration. Besides these advantages, SIFT method has some limitations that cause a large number of mismatches that greatly affect the process of registration. Many researches have been done in the literature to remove the mismatches in the SIFT algorithm [8] [9].

Random sample consensus (RANSAC) algorithm introduced in 1981 by Fischler *et. al*, is one of the most applicable methods for reduction of false matched points in the reference and sensed images [10]. RANSAC algorithm is very stable and capable to eliminate mismatches in the presence of noise. In addition to the advantages of RANSAC, it has some disadvantages, including high running time, the number of correct matches, and the dependency of mismatches removal on the amount of threshold value. Zhao *et. al*., suggested fast RANSAC method that improves the execution time compared to basic RANSAC [11]. Shi *et al.,* (2013) proposed a new method to improve RANSAC algorithm when the number of mismatches is high [12]. In this method, at first, using two other methods, some of the mismatches are eliminated and the rest of mismatches are eliminated using RANSAC algorithm. Li *et. al,* proposed a method for improving RANSAC in synthetic aperture radar (SAR) images [13]. In these images, due to speckle noise, many mismatched points are existed that reduce the performance of RANSAC algorithm. To solve this problem, an energy function is used to calculate the similarity between the feature points before using RANSAC algorithm, which makes the performance of the algorithm more robust. One of the disadvantages of RANSAC algorithm is that the threshold value is considered based on trial and error. In reference [14], this threshold value is set as 50, in reference [15] , this amount is set to 10, in reference [16], this amount is fixed and set to 1, and finally in reference [17] this amount is considered as 0.001. Determining the proper amount of threshold in RANSAC algorithm is an important issue, because if a small threshold value is selected, rate of true matches is decreased, and if a big value is selected, the rate of mismatches is increased, that has a serious effect on the results of image registration.

In this paper, improved RANSAC algorithm is proposed to eliminate mismatches. In this 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 of mismatches classes are maximized.

The organization of the rest of paper as follows. In the section II, the proposed method is described. In Section III, the simulation results is reviewed, and finally, the paper is concluded in section IV.

Zahra Hossein-nejad is with the Department of Electrical Engineering, Sirjan Branch, Islamic Azad University, Sirjan, Iran, (e-mail: hoseinnejad.zahra@yahoo.com)

Mehdi Nasri is with the Young Researchers and Elite Club, Khomeinishahr Branch, Islamic Azad University, Khomeinishahr, Iran, (Corresponding Author, e-mail: nasri_me@iaukhsh.ac.ir)

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II. Image Registration based on SIFT Features and Adaptive RANSAC transform

In this section, the improved RANSAC for image registration is introduced in detail. At first, basic RANSAC algorithm is reviewed, and then the proposed method is discussed in detail.

A. RANSAC Algorithm

This algorithm suggests a method for separating subset of correct matches, mismatches from among initial matching, and has application in removal of mismatches and estimation of parameters of the model transformation that will be discussed in the following section in more details.

First step: First, due to the differences between the reference and sensed images, it is necessary to select a suitable model based on the transformation model. The number of matched points that are required to calculate the various transformation parameters is calculated according to equation (1).

$$q = \frac{p}{2} \tag{1}$$

q is the minimum number of matched points required to calculate the transformation parameters, and p is the number of parameter in each transformation model. For example, in transformation of affine that needs six parameters, three matching points should randomly be selected for calculating the transformation parameters according to equations (2) and (3).

$$\begin{bmatrix} x_1 & y_1 & 1 \\ x_2 & y_2 & 1 \\ x_3 & y_3 & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} x'_1 \\ x'_2 \\ x'_3 \end{bmatrix} \tag{2}$$

$$\begin{bmatrix} x_1 & y_1 & 1 \\ x_2 & y_2 & 1 \\ x_3 & y_3 & 1 \end{bmatrix} \begin{bmatrix} d \\ e \\ f \end{bmatrix} = \begin{bmatrix} x'_1 \\ x'_2 \\ x'_3 \end{bmatrix} \tag{3}$$

In these relations, (x_1, y_1), (x_2, y_2) and (x_3, y_3) are the coordinates of the matching points in the reference image, and (x'_1, y'_1), (x'_2, y'_2) and (x'_3, y'_3) are the coordinates of the matching points in the sensed image and f, e, c, b, a are the parameters of the transformation model.

Second step**:** for the best model to be selected in the specified iterations, in each time iteration, three random matching points (in affine transformation) are selected to calculate the transformation parameters and in each iteration, based on transformation parameters obtained, the transformation model is calculated according to equation (4).

$$\begin{bmatrix} a & b & c \\ d & e & f \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix} = \begin{bmatrix} x'_1 \\ y'_1 \\ 1 \end{bmatrix} \Rightarrow \quad \begin{cases} x'_1 = ax_1 + by_1 + c \\ y'_1 = ax_1 + ey_1 + f \end{cases} \tag{4}$$

In these equations, f, e, d, c, b, a are the transformation parameters and (x_1, y_1) is the coordinate of matching points in the reference image and (x'_1, y'_1) is the coordinates of the transformation model in the sensed image that this transformation model can be written as HP_e where, H is transformation parameters and P_e is the matching points in the reference image.

Step Three**:** After calculating the transformation model parameters, for each matching point in the reference image, the distance between (P, HP_e) is calculated in the sensed image. If this distance is less than the threshold, this matching point is accurately matched; otherwise, the matched point in the reference and sensed images is deleted, and the tolerance error is empirically determined.

Step Four**:** In each iteration, the number of points that have been matched accurately is calculated. If the number of points that are accurately matched is more than the desired value, or reaches the predetermined maximum number of iterations, the algorithm stops. In the end, all the matching points, based on the transformation model that has the largest number of accurate matching, are again calculated.

B. Proposed method

The proposed method is considered as a classification problem for determining the threshold value, and its details are described in the continuation.

First Stage: (P, HP_e) distance which was expressed in the second stage of RANSAC algorithm, is calculated for all the matching points.

Second Stage**:** minimum, maximum and mean of the distance obtained in the first stage are calculated according to the equations (5) to (7).

$$\min(dis) = dis(P_i, HP_{ei}) \qquad (i = 1,2,\ldots,m) \tag{5}$$

$$\max(dis) = dis(P_i, HP_{ei}) \qquad (i = 1,2,\ldots,m) \tag{6}$$

$$mean(dis) = dis(P_i, HP_{ei}) \qquad (i = 1,2,\ldots,m) \tag{7}$$

In these equations, Pi is the ith matching in the sensed image, HP_{ei} is the ith reference match transformation model in the sensed image, and i is the number of matching points.

Third Stage**:** n number of thresholds are considered in the range from minimum to maximum, where the value of n just determines the threshold accuracy and does not have a great impact on the results of the algorithm. Here, the number of n is set to 1000. Afterwards, using equation (8), the distance of each threshold from another threshold is calculated and in accordance with equation (9), the value of each threshold is determined.

$$step = \frac{\max(dis) - \min(dis)}{n} \tag{8}$$

$$threshold(n) = (step \times n) + \min(dis) \tag{9}$$

In these equations, max (dis) is the maximum distance between the (P, HP_e) in all matching points and min (dis) is the minimum distance between (P, HP_e) in all matching points and n is the number of thresholds.

Fourth Stage**:** For all n threshold values, two classes are determined, and for each matching point, (P, HP_e) distance is calculated. If this distance is less than the threshold value, according to equation (10), it is placed in the first class (correct matches), and if this distance is greater than the threshold value, according to equation (11), it is placed in the second class (mismatches).

if dis (P, HP_{ei})< threshold (n) then matched point put in calss1 (10)
i=1,…,m

if dis (P, HP_{ei})> threshold (n) then matched point put in calss2 (11)
i=1,…,m

Fifth Stage: Then, for all n threshold values, variance of first class and the variance of the second class are calculated according to equations (12) and (13).

$$\delta_{1n} = \mathrm{var}\,iance(clase1) \tag{12}$$

$$\delta_{2n} = \mathrm{var}\,iance(clase2) \tag{13}$$

In these relations, δ_{1n} is the nth variance value in the first class, and δ_{2n} is the nth variance in the second class.

Sixth Stage: The goal of the algorithm is to decrease the variance in the first class (correct matches), and increase the variance in the second class. This makes distance values to be close to each other in the first class. On the other hand, if only the effect of variance is considered, maybe only one datum is located in the first class, and the variance became zero. To solve this problem, the average distance (P, HP_e) is also taken into account, where the threshold value should be close to the average value. This goal is implemented using equation (14).

$$f(n) = \frac{\delta_{1n} + |mean(dis) - threshold(n)|}{\delta_{2n}} \tag{14}$$

In equation (14), δ_{1n} is the n^{th} variance in the first class, and δ_{2n} is the n^{th} variance in the second class, and threshold (n) is the value of n^{th} threshold.

Seventh Step: Finally, to select the best threshold from among n thresholds, any threshold that has the lowest value, according to equation (15), is selected as the final threshold.

$$\varepsilon = \min(f(n)) \tag{15}$$

III. SIMULATION RESULTS

To evaluate the effectiveness of the proposed method, a series of experiments with different scale and rotations has been designed, and the results will be discussed with the correct matching rate and the rate of mismatches (false matches). To evaluate the performance of the proposed method, it is compared with threshold one in RANSAC algorithm [16] and threshold fifty in this algorithm [14]. Correct matching rate is calculated according to equation (16) and mismatch rate according to equation (17) and if the rate of correct match is high and mismatch is low, it is more suitable.

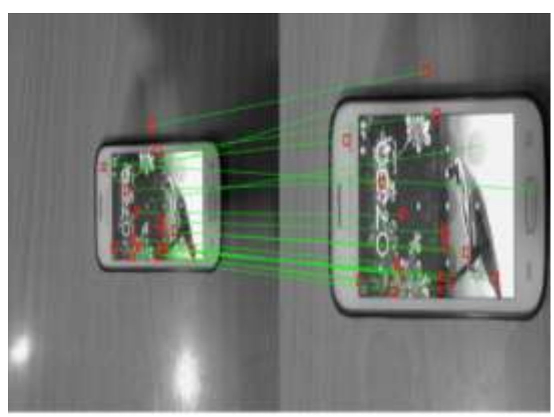
$$CMR = \frac{TP}{P} \tag{16}$$

$$FMR = \frac{FP}{P} \tag{17}$$

In these equations, TP is the number of correct matches, P is the total number of matching points, and FP is the number of mismatches.

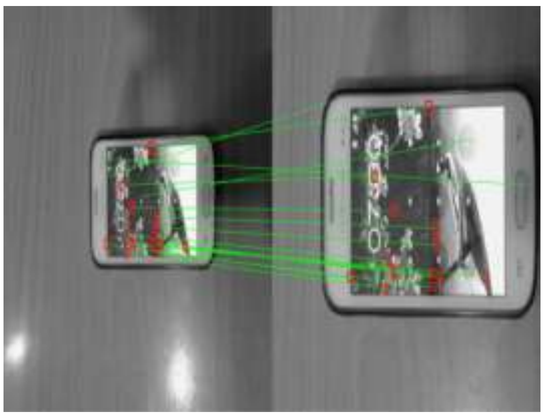
A. Different scale

In this experiment, a pair of images with different scales is used. The results of removed matches is shown in Fig. 1 that around the areas shown with squares in the figure, there are a number of correct matches mistakenly removed by the basic RANSAC algorithm.



(a)

(b)



(c)

Fig. 1. Eliminated matches images with different scales
(a) Threshold 1 (b) threshold 50 (c) proposed method

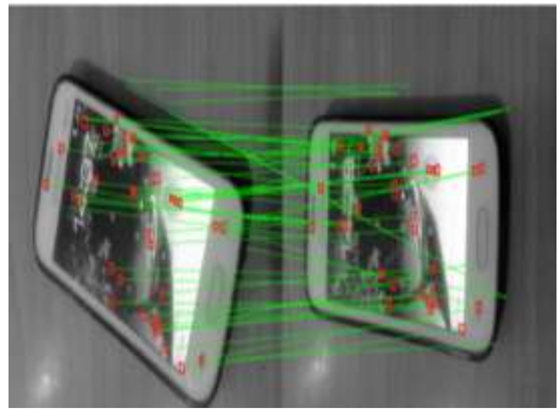
As Fig. 1 shows, RANSAC algorithm with different threshold values has different results. RANSAC algorithm with threshold one, in addition to the elimination of incorrect matches, eliminates a number of correct matches that would reduce the rate of correct matches. RANSAC algorithm with a threshold of 50, considers all matches as correct and eliminates none of the mismatches causing increased mismatch rate. RANSAC algorithm with the proposed method eliminates fewer correct matches, and leads to the higher correct matches' rate. The results of the evaluation are shown in Table I

TABLE I
THE RESULTS OF THE EXPERIMENT IN IMAGES WITH DIFFERENT SCALES WITH EVALUATION CRITERIA OF CORRECT MATCHING RATE AND THE RATE OF MISMATCHES

RANSAC with different threshold	**correct matching rate**	**mismatches rate**
threshold 1 [16]	0.733	0.020
threshold 50 [14]	0.948	0.051
proposed method	**0.804**	**0.10**

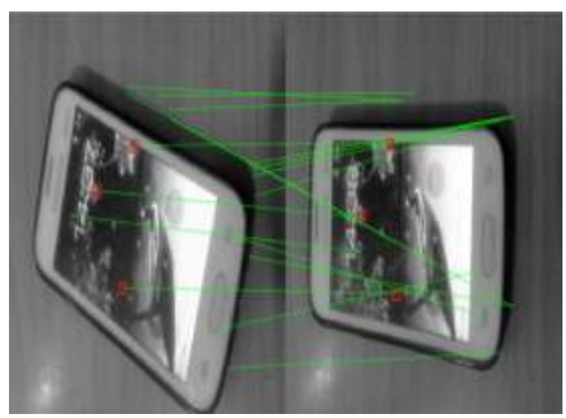
B. Different rotation

In this experiment, a pair of images with different rotation angles is used, and the results of the eliminated matches are marked in Fig. (2).



(a)

(b)



(c)

Fig. 2. Eliminated matches images with different rotation angles
(a) Threshold 1 (b) threshold 50 (c) proposed method

As Fig. 2 shows, in RANSAC algorithm with threshold one, a number of correct matches have been removed as a mismatch which reduced the correct matches' rate. The algorithm with a threshold of 50 considers all matches as correct, and as can be seen in Fig. 2, none of the mismatches has been eliminated, which increases the rate of mismatches. RANSAC algorithm with the proposed method in addition the elimination of mismatches, eliminates a small number of correct matches leading. The results are shown in Table II.

TABLE II
ELIMINATED MATCHES IMAGES WITH DIFFERENT ROTATION (A) THRESHOLD 1 (B) THRESHOLD 50 (C) PROPOSED METHOD

RANSAC with different threshold	**correct matching rate**	**mismatches rate**
threshold 1 [16]	0.50	0.060
threshold 50 [14]	0.825	0.174
proposed method	**0.8106**	**0.060**

IV. CONCLUSION

In this paper, the process of image registration is done by the SIFT method, and RANSAC algorithm is used to eliminate the mismatches. The main contribution of the proposed method in this paper is selecting the threshold in RANSAC algorithm adaptively. The results showed that by changing the threshold value in the RANSAC algorithm, the number of correct matching and removed mismatches is different in the algorithm. When, a large threshold value number is taken into account (for example, 50), all mismatches are considered as correct matches, and the rate of mismatch increases. When a small threshold amount is considered (for example, 1), a number of correct matches are eliminated and the rate of correct matches reduces. The proposed method leads to mismatch rate and correct matches control based on the variance maximization between correct matches and mismatch classes.

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