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Adaptive outlier elimination in image registration using genetic programming[☆]

Ik Hyun Lee[a,b,1], Muhammad Tariq Mahmood[c,*]

[a] Media Lab, Massachusetts Institute of Technology, Cambridge, MA 02139, USA
[b] Department of Mechatronics Engineering, Korea Polytechnic University, 237 Sangidaehak-ro, Siheung-si, Gyeonggi-do 15073, Republic of Korea
[c] School of Computer Science and Engineering, Korea University of Technology and Education, 1600, Chungjeol-ro, Byeongcheon-myeon, Dongnam-gu, Cheonan-si, Chungcheongnam-do, 31253, Republic of Korea

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ABSTRACT

In feature-based methods, outlier removal plays an important role in attaining a reasonable accuracy for image registration. In this paper, we propose a genetic programming (GP) based adaptive method for outlier removal. First, features are extracted through the scale-invariant feature transform (SIFT) from the reference and sensed images which were initially matched using Euclidean distance. The classification of feature points into inliers and outliers is done in two stages. In the first stage, feature vectors are computed using various distance and angle information. Feature points are categorized into three groups; inliers, outliers and non-classified feature (NCF) points. In the second stage, a GP-based classifier is developed to classify NCF points into inliers and outliers. The GP-based function takes features as an input feature vector and provides a scalar output by combining features with arithmetic operations. Finally, registration is done by eliminating the outliers. The effectiveness of the proposed outlier removal method is analyzed through the classification and positional accuracy. The experimental results show a considerable improvement in the registration accuracy.

1. Introduction

Image registration is considerably important in medical imaging and remote sensing applications such as image mosaicking and stitching, change detection (estimation of the damage from earthquake), and urban growth monitoring. It is an alignment between two or more images that are taken through single or multiple sensors. Generally, image registration can be classified according to sensor characteristics, transformation models and registration methods. If the reference and the sensed images are taken from the same sensor then the single-modal registration is commonly performed [31]. In many situations, the reference and the sensed images are taken from different sensors [16,22,28,31]. In this case, the multi-modal registration is more advantageous than the single-modal registration. However, the multi-modal registration is more com-

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* Corresponding author.
E-mail addresses: ihlee@kpu.ac.kr (I.H. Lee), tariq@koreatech.ac.kr, mtariqm75@gmail.com (M.T. Mahmood).
[1] He is currently an assistant professor at Korea Polytechnic University.

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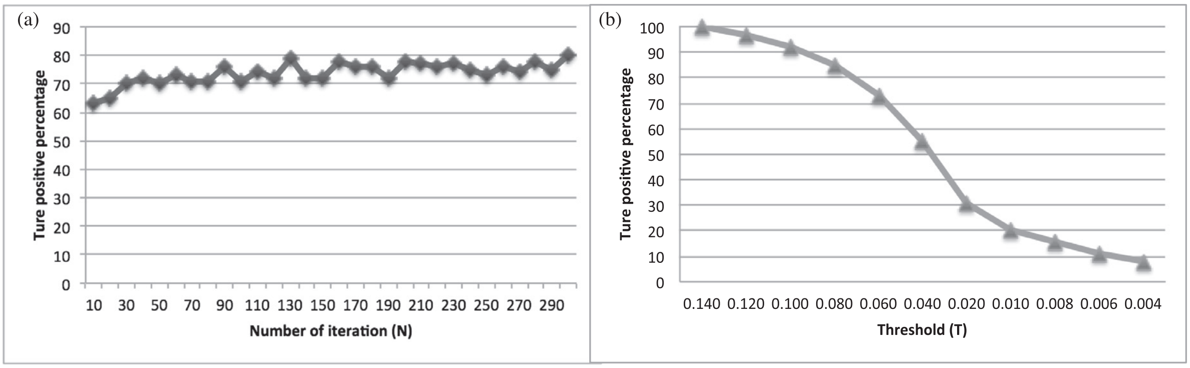

Fig. 1. RANSAC results of varying: (a) number of iteration (*N*) with threshold 0.06, (b) threshold (*T*) with number of iteration 100.

plicated as compared to the single-modal registration as different sensors may have diverse characteristics and image pixel intensities [31]. Transformation models can further be classified as global and local models. In global transformation models, rotation and translation transformations are included. On the other hand, a local transformation is used for warping the target image to align with the source image [31].

In general, the registration methods can be categorized into two main categories; intensity-based and feature-based methods. Intensity-based methods compare the pixel intensities of the overlapping regions in images by using a similarity measure such as sum of squared difference (SSD) and mutual information (MI) [16,22,28]. In these methods, similarity measure plays an important role and the accuracy of the method depends on choosing an appropriate similarity measure. On the other hand, feature-based methods use features (points, lines, intersections, etc.) instead of pixel intensities from corresponding regions of one or more images [31]. These feature-based methods usually undergo five steps to register two images of a scene: (1) pre-processing, (2) feature extraction, (3) feature matching, (4) estimation of transformation, and (5) re-sampling. In the pre-processing step, image processing operations such as image smoothing, de-blurring and segmentation are performed to enhance the image. In the feature extraction step, useful information (features) such as points, lines, regions and templates are extracted from the images. In the feature matching step, the correspondence between the selected features is determined on the bases of feature's similarity. In the transformation step, appropriate parameters are determined from the corresponding features. Finally, in the re-sampling step, the sensed image is re-sampled according to the source image.

In feature-based methods, there are two key factors that affect the accuracy, and they need to be considered appropriately. The first factor is to extract features with desired numbers and distribution. The second factor is to extract accurate corresponding features or minimize the incorrect corresponding features (outliers). In order to obtain the desired number of features, Wong and Orchard [28] used modified Harris corner detector after applying the local normalization. Then, they selected the first one hundred strongest feature points for correspondence. Many researchers have used the scale-invariant feature transform (SIFT) [16] and its variants for image registration [22]. To get the desired numbers and distribution of the feature points, Sedaghat et al. [22] suggested a modification in parameters for computing SIFT features. While, these tactics work well for normal images; however, in the registration of remotely sensed images, these methods perform poorly as they use limited number of feature points. Whereas, larger number of feature points are important for better accuracy in satellite image registration [7,10,37,39].

The second factor that affects the accuracy of feature based methods is the elimination of outliers. In general, an outlier is a data point or an observation which is significantly deviated from the remaining data [9,32,35]. Outlier detection is a critical task and a variety of statistical and machine learning based methods are available for differentiating the outliers from the consistent data. Mainly, these methods can be categorized into three types depending on the availability of information regarding the data. Type-1 of outlier removal methods deal with data with no prior knowledge. Unsupervised machine learning methods such as clustering and subspace methods are used for outlier detection. Usually, in type-2 methods, a set of labeled examples are available and supervised machine learning can be used to learn a classifier for outlier detection. Type-3 methods learn only single class and generally use semi-supervised learning methods [9]. In image registration, a statistical based method, random sample consensus (RANSAC) [5], is commonly used for eliminating outliers [11,12,27,30]. In RANSAC, the numbers of samples are adaptively set because the proportion of outliers is determined from each consensus set. RANSAC works well with both small and moderate numbers of different correspondences and outliers; however, its performance gets degraded in case of large numbers of correspondences. Moreover, the performance of RANSAC highly depends on the number of parameters including number of iterations, distance threshold, desired confidence, and inlier percentage.

Fig. 1 shows the influence of the two parameters, number of iterations and distance threshold, in RANSAC on the classification accuracy using the synthetic data. Similar evaluations and representations can be found in [20]. Kim and Im [12] used RANSAC for a robust estimator in the presence of outliers and experimented with real data. Their procedure uses RANSAC