Applied Computer Systems
ISSN 2255-8691 (online)
ISSN 2255-8683 (print)
December 2023, vol. 28, no. 2, pp. 252–257
https://doi.org/10.2478/acss-2023-0025
https://content.sciendo.com

A Rigid Image Registration by Combined Local Features and Genetic Algorithms

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***Abstract* – Image registration is an essential pre-processing step required for many image processing applications such as medical imaging and computer vision. The aim is to geometrically align two or more images of the same scene by establishing a mapping that relies on each point from one image to its corresponding point of another image. Scale invariant feature transform (SIFT) and speeded up robust features (SURF) are well-liked local features descriptors that have been extensively utilised for feature-based image registration due to their inherent properties such as invariance, changes in illumination, and noise. Moreover, the task of registration can be viewed as an optimization problem that can be solved by applying genetic algorithms (GAs). This paper presents an efficient feature image registration method based on combined local features and GAs. Firstly, the procedure consists of extracting the local features from the images by combining SIFT and SURF algorithms and matching them to refine the feature set data. Therefore, an adaptive GA based on fitness sharing and elitism techniques is employed to find the optimal rigid transformation parameters that best align the feature points by minimizing a distance metric. The suggested method is applied for registering medical images and the obtained results are significant compared to other feature-based approaches with reasonable computation time.**

***Keywords* – Combined local feature points, genetic algorithms, image registration, rigid transformation.**

I. Introduction

Image registration is a demanding task in computer vision and image processing. It is the process of overlaying two or more images of the same scene taken at different times, from different viewpoints, and/or by different sensors [1]. The purpose is to spatially align images by removing or suppressing geometric distortions that were produced by differing imaging conditions. This has been applied in many fields such as those involving medical image analysis [2], [3] and remote sensing data [4], [5].

Depending on the information used, the image registration techniques generally can be split into two basic categories: intensity-based and feature-based methods. Owing to their various advantages as brevity, simplicity, and low computational complexity, feature-based methods are more frequently used than intensity-based methods [3]. In this way, feature-based registration entails determining the geometric transformation that spatially aligns the corresponding features of the images. The geometrical transformation can be classified into the rigid transformation and the non-rigid transformation according to whether there are feature deformations or not. The rigid or affine transformation is often used to initialize the spatial alignment [6]. Generally, the following steps are included in most registration procedures: A set of pertinent features that can be represented by their point representatives are identified from the two images via the feature space. The class of transformations known as the search space can align the images. The relative merit of the match is determined by the similarity metric. To increase the matching criterion, the parameters of the transformation are changed during the optimization phase. The search is carried out based on this finding until an optimal transformation is discovered with a suitable similarity measure. An extensive overview of registration methods used typically for medical images is provided in [7], [8], [9].

A wide range of feature extraction techniques has been developed in the literature for identifying prominent and reliable descriptors in images. The two most effective methods are SIFT (scale invariant feature transform) and SURF (speeded up robust features) [10], [11]. Both approaches create invariant descriptors that can be used to identify and match interest points or so-called features even when faced with a range of distracting circumstances, including scale changes, rotation, changes in illumination or viewpoints, or image noise. A significant number of descriptive features may be produced via the SIFT feature extraction technique, which raises the proportion of accurate matches. The effectiveness of the SIFT algorithm has been affirmed by various research works as in [7], [12], [13]. Similarly, studies have addressed the use of SURF for feature detection in medical images [14], [15].

Image registration is still a difficult area of study. Three key factors that limit the applicability of universal registration techniques are registration accuracy, reliability, and computational time [16]. SIFT has performed well in the detection and description. However, the whole process is time-consuming [10]. Otherwise, SURF has proved its superiority compared to SIFT in terms of runtime efficiency while still yielding comparably good results with regard to feature point quality. Combining SIFT and SURF algorithms appears as a

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potential solution to achieve good performance in an acceptable time.

Recently, an extraordinary interest has been sparked by the use of numerous well-known evolutionary algorithms due to the nature of their global stochastic optimization. Among them, genetic algorithms (GAs) present an effective method that can scour a big search space and focus its search on areas that provide better solutions to the issue. A lot of work has addressed the application of GAs especially for medical image registration [17], [18], [19]. This study proposes a completely automatic feature image registration technique that integrates combined local features based on SIFT and SURF to extract feature sets and GAs to find the optimal rigid transformation parameters. The algorithm is applied to register two medical images. The remainder of this article is structured as follows: The framework of the proposed registration technique is described in the second part in which we give an overview of local features and the genetic optimization procedure employed in this study. The third section is devoted to the formulation of GAs components for image registration. In the fourth section, the outcomes of the simulation are provided and, lastly, we conclude this study.

II. Image Registration Methodology

Our image registration technique is composed of two main parts as described in Fig. 1.

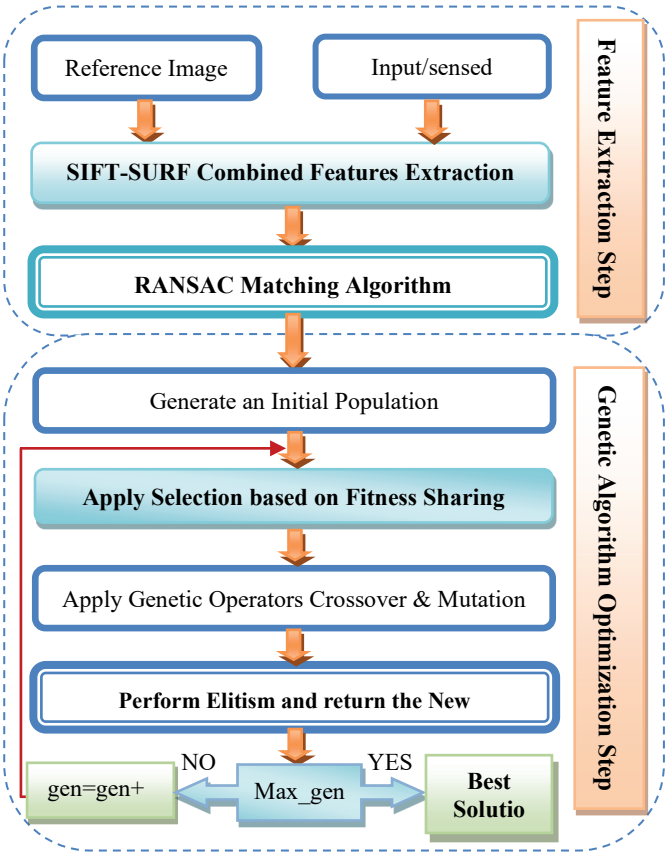
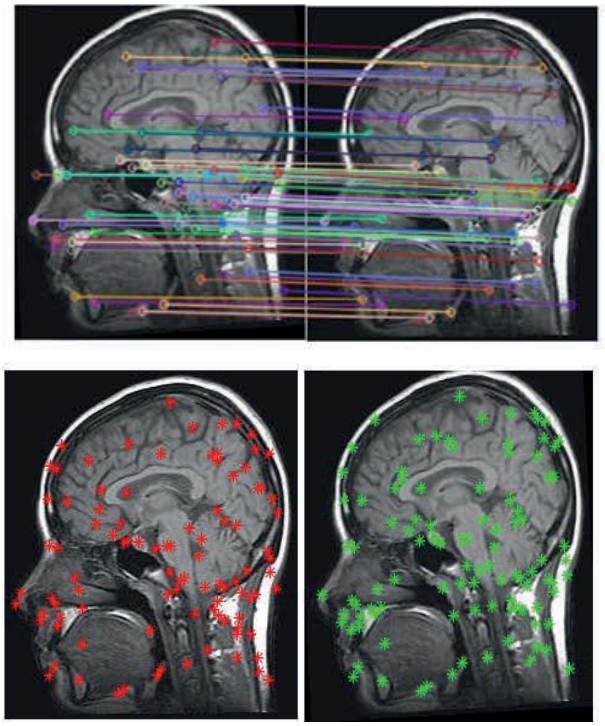


Fig. 1. Framework of the proposed image registration technique.

Given the two images to be registered, the first image is referred to as the reference image, while the second image is commonly referred to as the input or sensed image. The first stage consists of feature extraction from both images based on combined local invariant features using SIFT and SURF algorithms. The second stage comprises the optimization cycle by using an adaptive genetic procedure to estimate the best solution to the registration problem. In this section, we focus on the details of these two parts of the suggested method.

A. Local Feature Extraction and Matching

SIFT has been presented by Lowe in 2004 [20]. It effectively recovers unique local features that can be used to match objects across images. Based on the gradient magnitude and relative direction in the local neighbourhood of pixels, a feature description is generated for each key point [21]. Similar to SIFT, SURF is a local invariant fast feature point detector and distinctive feature point descriptor [22]. The initial phase of processing assigns an orientation inside a circular zone around the key point. The SURF descriptor is then computed once a squared region is aligned to the chosen orientation using Haar wavelets responses. In this study, we utilise a combination of SIFT and SURF algorithms to identify the feature points in which SIFT detects key points and SURF builds the key point descriptors.



Num outliers reported by RANSAC = 38
Num inliers reported by RANSAC = 78

Fig. 2. Feature point extraction and matching based on SIFT-SURF and RANSAC algorithms of MR images.

Once features have been detected in the two images, the next step is to match them or identify correspondence between pair

features. RANSAC (Random Sample Consensus) algorithm is a famous algorithm used for matching to eliminate false-matching points [23]. Although the data set contains a significant number of outliers, it is still able to estimate the parameters accurately [24]. In this study, the process of matching is performed using the open-source computer vision library using the conventional RANSAC algorithm and a pre-matching mechanism based on the Brute Force technique. An example of feature extraction and matching is illustrated in the Fig. 2 of two magnetic resonance (MR) images in axial plane of size 253×238 pixels.

B. The Proposed Optimization Algorithm

GA refers to the natural genetic system. GA [25] is a computer-based simulation algorithm of natural evolution that employs biological principles as heuristic search techniques. The natural selection theory states that those who are more adapted to a certain environment have a higher chance of surviving. In the GA process [26], an initial population of chromosomes is created randomly (often in the form of a bit string). Over multiple generations, the chromosomes evolve and hence new offspring are produced through the use of the crossover and mutation operators. Crossover involves breaking two chromosomes, whereas mutation entails flipping a single chromosomal bit. Each chromosome is assessed using the objective function of the problem, and a fitness value is given to it. The most fitted chromosomes are more likely to be chosen and employed to create the following generation. The operation is repeated until a predetermined termination criterion is met.

GA is an intelligent global stochastic search and optimization technique that can focus its search on areas that lead to better-fitting structures and thus better solutions for the problem by examining a broad solution space. However, GAs present some disadvantages. The major limitations of GAs are the slow convergence speed and the risk of premature convergence. To maintain the diversity of the population and prevent the loss of the best individual throughout the GA procedure, two promising approaches are adopted in this study, namely, fitness sharing and elitism.

Fitness Sharing Technique. Fitness sharing is a popular and effective way that allows guiding the search process in unexplored regions by clustering the population into different subgroups according to the similarities of the individuals. The fitness values are more degraded when the individuals are more concentrated around a certain individual. Consequently, a non-dominated solution set is built in an objective space within a uniform distribution [27].

Mathematically, the shared fitness of individual i is defined as follows:

$$f_{\text{shared}}(i) = \frac{f(i)}{\sum_{j=1}^{m} \text{sh}(d_{ij})}, \tag{1}$$

where m denotes the population size, d_{ij} represents the distance between the individual i and j, and sh describes the sharing function. The latter measures the similarity level between individuals according to a threshold of similarity σ_s (usually given by the user) corresponding to this expression [28]:

$$\text{sh}(d_{ij}) = \begin{cases} 1 - \left(\dfrac{d_{ij}}{\sigma_s}\right)^{\alpha} & \text{if } d_{ij} < \sigma_s \\ 0 & \text{Otherwise} \end{cases} \tag{2}$$

α is a constant parameter that regulates the sharing function shape (typically $\alpha = 1$).

Elitism Technique. In the basic GAs, the best chromosome found in the succeeding generation may be lost because of the probabilistic characteristics of the genetic operator selection, crossover, and mutation. To overcome this problem, we use the elitism technique. Preserving the best solutions gained during the optimization process avoids losing the fittest individuals discovered. It is a useful tool for enhancing GA performance capacity.

III. GAs Formulation for Image Registration

The formulation of the chromosome and fitness function is crucial for GAs to be successful. The structure of these components for the considered feature-based image registration task is explained in this section.

A. Chromosome Encoding

For the image registration optimization problem, every individual (chromosome) from the population represents a combination of all rigid parameters that describe an image transformation. Then to represent a chromosome in an iterative process, the vector of parameters (R, X, and Y) is employed where R depicts the rotation and (X, Y) represents the translation in the x and y directions. A bit encoding is adopted in this study. R is represented by an 8-bit field, while X and Y are represented by a 6-bit field as shown in Fig. 3. The high-level bit is used for the sign and the remaining bits are used to denote the magnitude of the rotation or translation in all forms. The resulting ranges for the relative rotation and translation in the x (or y) direction are 127 degrees and 31 pixels, respectively. Thus, we have 2^{20} different possible combinations.

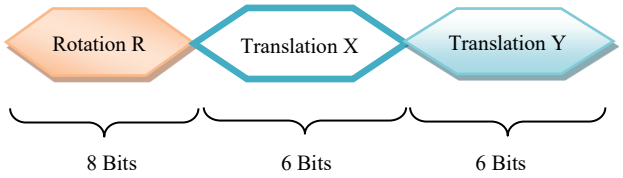


Fig. 3. Chromosome encoding scheme.

B. Objective Function

GA evaluates each chromosome performance using a fitness function. Formally, our registration technique determines the rigid transformation parameters that minimize the cost function. Given the two feature sets extracted previously, the model set M is generated from the reference image, and the scene set P is

delivered from the input image. To assess the registration dissimilarity between the two feature sets, an error distance function is utilised. Therefore, GAs should attempt to identify the chromosome with the smallest distance between each pair of correspondences.

Considering the transformation parameters (R, X, Y), each feature point P_i in the model P is related to its transformed image point P_t by the following mapping:

$$P_t = \begin{bmatrix} \cos \mathrm{R} & -\sin \mathrm{R} \\ \sin \mathrm{R} & \cos \mathrm{R} \end{bmatrix} \cdot P_i + \begin{bmatrix} \mathrm{X} \\ \mathrm{Y} \end{bmatrix}. \quad (3)$$

Thus, the objective is to minimize the Euclidean distance between each transformed point P_t in P and m in the M data set. Hence, the root mean square error (RMSE) metric is chosen as the fitness function of the registration problem given by this formula:

$$RMSE = \sqrt{\frac{\sum\sum_{i=1}^{n} m_i - P_t^2}{N}}, \quad (4)$$

where N represents the total number of feature points.

IV. Simulation Results and Discussion

To demonstrate the performance of our algorithm, we have conducted two experiments. The first one is devoted to registering two MR medical images in an axial plane with simulated transformation parameters; and the second one is dedicated to a real application for registering diabetic foot images.

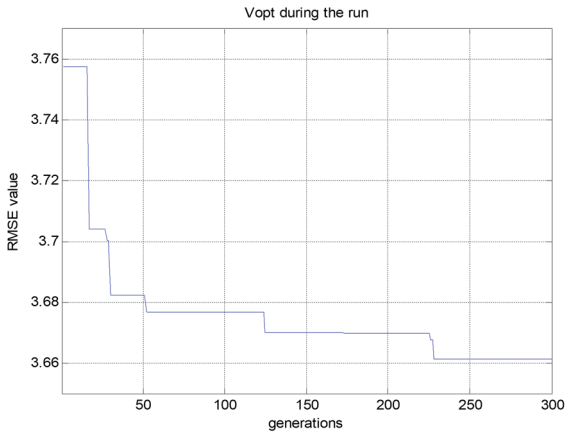
The experiments have been implemented in MATLAB software using the software package "mexopencv". All the tests were conducted on a personal computer, Intel Core i3 CPU 2.53 GHz with 4.00 GB available RAM. Table I depicts the GA parameters used in our simulations.

TABLE I
GA Parameters

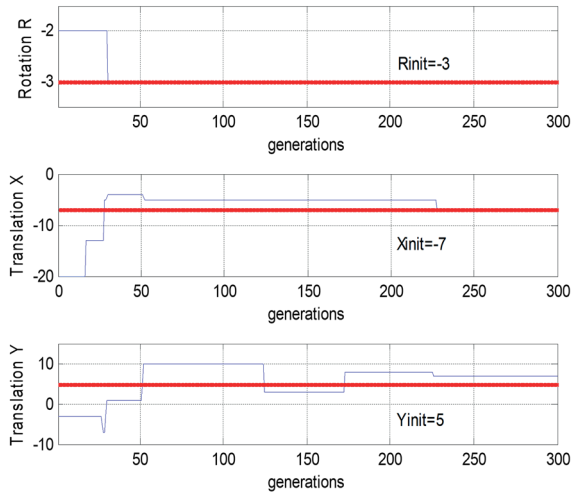
Parameters	Type	Value
Population size	Binary	80
Max generations	/	300
Fitness	Sharing	$\sigma = 1.2$
Crossover	Two point	$P_c = 0.75$
Mutation	Flip flop	$P_m = 0.05$
Elitism	/	5 %

The First Experiment. To prove the capability of the suggested image registration algorithm, a simulated test was performed with known geometrical transformation parameters (rotation, translation). The resulting transformed image to be corrected was rotated by 3 degrees using bilinear interpolation, and displaced by 7 and -5 pixels in X and Y directions, respectively, from the centre of the reference image.

Figure 4 illustrates the GA process performance throughout the iterations applied to MR images. Figure 4(a) depicts the evolution of the fitness value (RMSE) of the best solution. It is clearly shown from this figure that the fitness value progressively decreases during the generations until the optimal fitness value is found corresponding to the best solution gained at the maximum iteration. Figure 4(b) displays the evolution of the rigid transformation parameters (R, X, Y) across the generations. The initial parameters are represented by the red dashed lines, while the best parameters discovered by the GAs running are indicated by the blue lines. The results clearly show that the optimal transformation parameter values found by GAs are quite close to the original parameters. This proves the effectiveness of our feature image registration technique based on GAs.



(a) Fitness value evolution of the best solution.



(b) Evolution of the transformation parameters (R, X, Y).

Fig. 4. GA performance during the process run.

Furthermore, a comparison is conducted with other feature extraction techniques such as SIFT and SIFT-BRIEF. Table II resumes the analytical results found with the different computing techniques in terms of the number of feature points matched, RMSE, correlation coefficient, and time consuming.

TABLE II
ANALYTICAL RESULTS OF THE COMPUTING METHODS

	SIFT	SIFT&SURF	SIFT& BRIEF
Matched Features	423	**78**	261
RMSE	3.6637	**3.6586**	3.6615
Corr	0.8907	**0.8915**	0.8910
Time (s)	4.3676	**3.1364**	3.9388

It can be seen from the table that the combined local features technique based on SIFT-SURF algorithm outperforms the other competing techniques in terms of precision and time processing. The values of RMSE and normalized correlation coefficient are very close but the combination of SIFT-SURF achieves the best results. Owing to the huge number of feature points matched, SIFT has the biggest time running compared to others.

Figure 5 shows two images to be aligned, reference and transformed images, and the resulting registered image with the optimal parameters obtained using the proposed method.

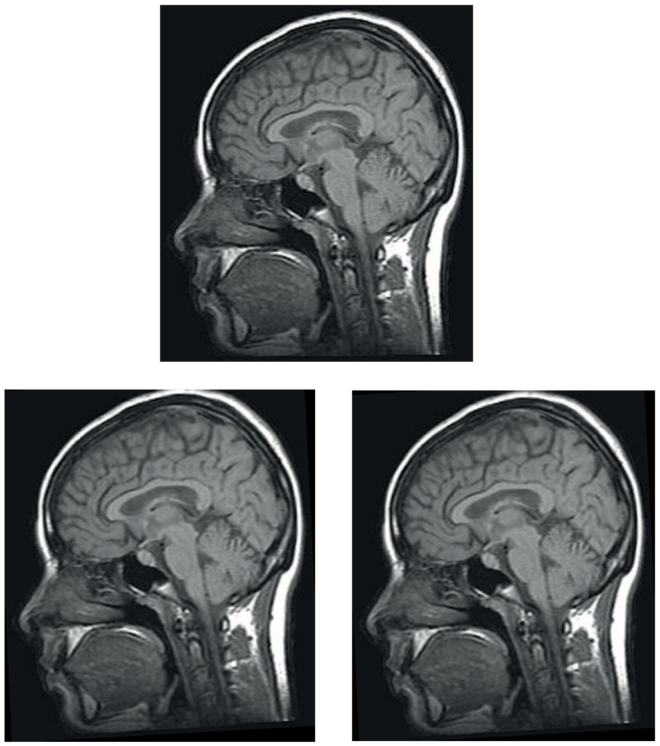


Fig. 5. The registration results of MR images: at the top the reference image, at the bottom left the transformed image, and at the bottom right the registered image with the proposed algorithm.

The Second Experiment for Real Application. In this experiment, we applied the proposed feature registration algorithm based on the adaptive GAs for registering two diabetic feet. In this case, we should note that a pre-processing of the images is required to adjust the intensity illumination. Figure 6 presents the different images issued in this implementation. The original image represents the two feet to be compared. The right foot is considered the reference image and the left foot is identified as the target image to be corrected. The left foot is flipped horizontally to look like the right foot. The correlation coefficient obtained between the registered image with optimal transformation parameters found and the reference image is about $r = 0.8690$.

Even though registration is not always optimal due to asymmetrical feet, we are satisfied with our registration results.

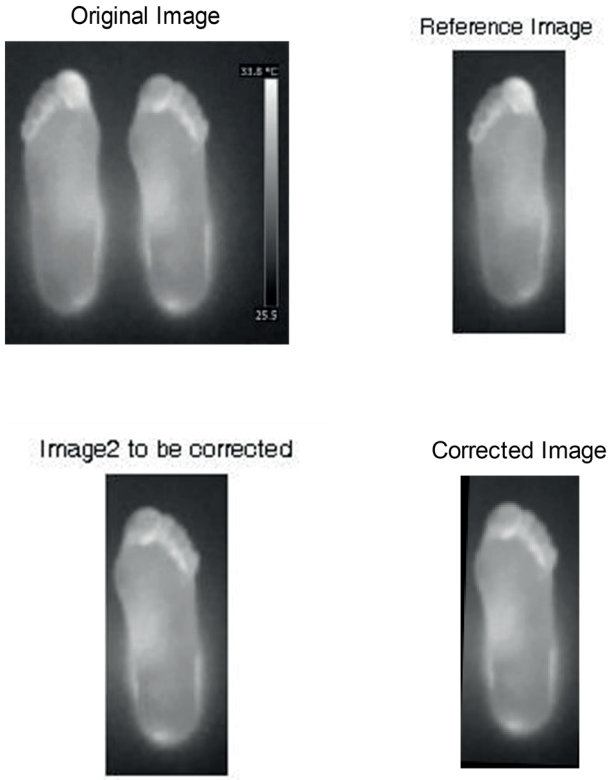


Fig. 6. Registration results of foot images: Original image representing the two diabetic feet, Reference image representing the right foot, Input image to be corrected representing the left foot, and corrected image with our proposed method.

V. CONCLUSION

A local feature-based image registration technique was developed in this study. The feature sets were established using a combined local feature extraction approach that combines SIFT as a detector and SURF as a descriptor. Then, GA was performed to optimize the rigid transformation parameters by minimizing the distance between the two feature sets. The proposed technique was applied to register medical images and the results are satisfactory. Our objective was to demonstrate the capability and robustness of GAs and to prove the effectiveness of the SIFT-SURF algorithm. In our future works, we will focus on elaborating a registration technique within a multi-objective scheme that optimizes both the matched feature points and the transformation parameters.

VI. ACKNOWLEDGMENTS

The authors express sincere gratitude to Pr Rachid Harba of Institute PRISME, Université d'Orléans, France, for his collaboration and for providing the feet image for our test.

VII. Disclosure Statement

The research being reported in this publication was supported by the Algerian Directorate General for Scientific Research and Technological Development (DGRSDT).

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