CHAPTER 5

COMPARISON OF PROPOSED REGISTRATION ALGORITHMS FOR DETECTING RVO

The retinal image registration plays a vital role in diagnosing various diseases apart from aiding in therapy planning. The literature review has revealed that more research has been undergone on retinal disorders due to diabetic retinopathy and macular edema whereas the work related to occlusion is comparatively less. But retinal occlusion is reported as the second largest retinal disorder all over the world. This work aims at developing new registration algorithms to detect occlusion at the earlier stages of the disease. The retinal occlusion may occur in either the retinal artery or retinal vein. Retinal Vein Occlusion is more common and called as RVO by the ophthalmologists. The occlusion occurring in the central vein, which affects the entire retina is called as Central Retinal Vein Occlusion (CRVO) and the occlusion in the branch retinal vein is named as Branch Retinal Vein Occlusion (BRVO). The symptoms and consequences are different in both the RVOs.

The previous chapter has explained the methodologies of registering the retinal images affected with occlusion. CRVO images are found to be registered with more accuracy using RANSAC matching algorithm and BRVO images are registered perfectly using BPSO algorithm. The techniques used to optimize the similarity metric in both the types are chosen in such a way that it matches the anatomical and pathological requirements of the input retinal image from the ophthalmologists. These techniques are tested on different set of images available from the database and collected from various eye hospitals.
DRIVE and STARE database are the readily available retinal images that are subjected to testing and evaluation by all the researchers in this field. DRIVE database is a collection of twenty images with retinal disorders and STARE database has four hundred test images. Two hundred images at various pathological conditions are chosen from this database to evaluate the proposed registration algorithms and found to be satisfactory. Retinal images affected by occlusion are also collected from various hospitals and detailed in Table 5.1. This chapter compares and evaluates various registration algorithms and optimization techniques discussed from Chapter 2 to Chapter 4. The overall performance of various proposed registration algorithms for different sets of test images are shown in Table 5.2.

### Table 5.1  Database of test images

<table>
<thead>
<tr>
<th>S.No.</th>
<th>Retinal Image Database</th>
<th>Source of Image</th>
<th>No. of images affected with CRVO</th>
<th>No. of Images affected with BRVO</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Set 1</td>
<td>DRIVE</td>
<td>8</td>
<td>12</td>
</tr>
<tr>
<td>2</td>
<td>Set 2</td>
<td>STARE</td>
<td>80</td>
<td>120</td>
</tr>
<tr>
<td>3</td>
<td>Set 3</td>
<td>Real Time Images from Ophthalmologists</td>
<td>50</td>
<td>50</td>
</tr>
</tbody>
</table>

### Table 5.2  Comparison of success rate for various methods

<table>
<thead>
<tr>
<th>Retinal Image Database</th>
<th>MIREB with SA</th>
<th>MIREB GA</th>
<th>RANSAC with GICP</th>
<th>BPSO-DF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Set 1</td>
<td>90.12</td>
<td>93.45</td>
<td>94.16</td>
<td>94.78</td>
</tr>
<tr>
<td>Set 2</td>
<td>91.34</td>
<td>93.65</td>
<td>93.9</td>
<td>95.12</td>
</tr>
<tr>
<td>Set 3</td>
<td>40.65</td>
<td>42.14</td>
<td>76.65</td>
<td>80.32</td>
</tr>
</tbody>
</table>
5.1 PERFORMANCE OF SA AND GA BASED REGISTRATION

Any image registration technique will be either an area based technique or a feature based technique. The former registers the input image with respect to the reference image by maximizing the similarity metric identified to be common between these two images based on any statistical measures like cross correlation, mutual information, etc. The latter registers the two images based on the common features that appear similar between these images like points, lines, contours, etc. But these two techniques have their own shortcomings when applied to the retinal images. The major drawbacks of applying these techniques to the retinal images are

1. The retinal images are subjected to non uniform illumination during image acquisition, which leads to non uniform intensity variations. Hence the area based techniques register with an accuracy level less than 60%.

2. The feature based techniques involves the identification of similar features between the images, but the retinal images is filled with complicated bifurcations and crossover points which makes the feature extraction process tedious.

Therefore a new technique of combining both the feature based and area based techniques are developed and explained in Chapter 2. This technique involves the extraction of blood vessels (features) from the retinal images and applying mutual information (area) on these extracted bifurcations to register them (MIREB). This similarity metric is maximized by two different optimization approaches: Simulated Annealing and Genetic Algorithm.
5.1.1 Simulated Annealing

Simulated annealing is a flexible optimization technique used to solve combinatorial problems. Simulated annealing emulates the process of annealing in metals and was initially proposed for solving problems in statistical mechanics. The major merits of this technique are that it can be used in solving plenty of problems regardless continuity, convexity, and differentiability. The registration of retinal images is done by maximizing the mutual information after extraction of the blood vessels. Mutual information is a function of the entropy and joint entropy of the two images. Simulated annealing is used as an optimization tool to maximize the mutual information. This technique has a major advantage of admitting worst solution rarely which eliminates local optima especially in a large and discrete search space like the retinal image with numerous bifurcations.

Simulated annealing is adaptable to the varying run time parameters like the cooling rates, Markov chain length and the stopping criterion are adjustable with respect to the input image characteristics. The extracted blood vessels of the input image are to be geometrically aligned with respect to that of the reference image. Literature analysis has revealed that affine transformation best suits for retinal images as it preserves parallelism in line to line mapping with six degrees of freedom. The generated neighborhood population can be reached from any point in the search space through Markov walk as the step size is a function of the width and height of the search space besides the acceptable number of rotations and scaling. The search is stopped when there is no tangible improvement in the Markov chain entry and the acceptance ratio is below 0.3. The registration results when tested with the DRIVE and STARE database are found accurate and reported with an average success rate of 90.12% and 91.34% respectively. But when this algorithm is tested in real time retinal images from set 3 the success rate is less than 50%. The real time images are subjected to high level spontaneous emission noise.
and the extraction of bifurcations could not be successful in such images, leading to misalignment. Such misalignments lead to complexity in the calculation of step size which includes the search space dimensions along with the maximum number of rotations and scaling.

5.1.2 Genetic Algorithm

Genetic Algorithm is an evolutionary optimization technique used to optimize discrete problems. GA varies from SA by replacing the variables with their encoded values. The solutions are not individuals, but termed as population which is a collection of chromosomes with maximum similarity and fitness value. Genetic algorithm is used to overcome the problem of local optimum due to the spatial dependence of the mutual information function.

The retinal images affected by occlusion are subjected to segmentation by which the blood vessels are extracted. Now mutual information based registration is attempted on these extracted segments. The maximization of mutual information is achieved by applying GA by carefully choosing the population P with size N in a search space S. These chromosomes are binary bit strings and the encoded length of this string determines the precision and computational time. The exclusive individual of the population is preselected and the crossover is done pairwise. The domination of the super individuals, i.e. the chromosomes with maximum fitness value is reduced by scaling the objective function. A new improved population is created in the recombination phase through crossover which combines the goodness of better chromosomes. The diversity of the population is maintained throughout by encoded mutation and GA uses the probability function whereas SA implies derivative function.

This makes the evaluation procedure to be concerned at the computational time. The major controlling parameters of GA are the population size N, Cross over probability $p_c$ and probability of mutation $p_m$. 
The retinal image registration using mutual information involves the minimization of the joint entropy between the test and the reference images. The intensity of the bifurcations shows a wide range of variation due to the impact of occlusion in which flame shaped hemorrhages exist throughout the blood vessel. The difficulty in geometrical alignment due to worst intensity variations is addressed by encoded mutation in GA. The experimental results have shown that the registration accuracy is increased when the images are registered with GA rather than SA. The success rate for retinal images in set 1 and set 2 is approximately 93%, whereas the success rate is less than 50% in set 3 (real time images). The registration accuracy is not improved even after modifying the population size and carefully assigning the initialization procedure.

From the experimental results of registration using SA and GA it is understood that the registration accuracy can be improved by adapting a suitable segmentation technique and modifying the registration algorithm rather than varying the optimal tools. Hence adaptive multispectral thresholding is used to segment the blood vessels of the retinal images affected with CRVO.

5.2 PERFORMANCE OF RANSAC GICP BASED REGISTRATION

The iterative closest point algorithm is extensively used in registration of medical images. ICP algorithm aims at reducing the distance between the two clouds of points by performing rotational and translational transformation. When the blood vessels of the input retinal image are matched with the blood vessels of the reference retinal image the ICP algorithm iteratively reduces the distance between the reference points and the target points. The performance of ICP depends on various parameters like the number of points selected, matching and weighting with respect to each point,
error metric of the transform, minimizing the error metric and rejecting the outliers. When the retinal images of set 1 and 2 are tested with ICP it is observed that the registered output is stable with less number of outliers. But when tested with images from set 3 there is a transient decrease in the stability due to the intolerance to the noise level.

To increase the tolerance level to noise and reduce the outliers, the ICP algorithm is slightly modified to accept the gradient information of the input data. This gradient ICP is effective on the database images, but reported with reduced efficiency in real time images because of the maximum initial misalignment between the reference and input retinal images. The limitations of instability, sensitivity to noise and misalignment are attempting to overcome by using RANSAC matching.

5.2.1 RANSAC Matching

RANSAC matching is extensively used in computer vision for the robust feature detection, extraction and matching. The main advantage of this method is that it does not depend on the geometrical features as they are environmental dependent. It is also unique that it uses small initial data set and consistently enlarges the data set rather than initializing a large volume of data and eliminating invalid data. Such characteristics of RANSAC matching exerted to experiment retinal image registration of real time images using RANSAC matching.

When the real time retinal images affected by occlusion are tested with RANSAC matching, the statistical geometric distribution of the input data is determined. The probability of success on each trial is evaluated with a constraint that the probabilities of each data point occur within the error tolerance. Thus the registration accuracy improved effectively by combining
RANSAC matching and gradient ICP. The overall success rate increased approximately 10% when tested with all the three sets of retinal images.

5.2.2 Challenges with Real Time Images

Even after modifying the variants of gradient ICP the success rate of registration could not be increased above 90% for repeated trials. The step by step analysis of this algorithm for different sets of retinal images revealed that some images are registered with an accuracy above 94% and some are below 65% for the same algorithm. The ophthalmologists recommended that the pathological impact will differ in CRVO and BRVO images. The CRVO images reported with leaking blood vessels throughout the retinal surface, whereas the BRVO images appeared with blood leakage only in the affected area. The experimental results proved that RANSAC matching based gradient ICP worked well for CRVO images, but with reduced accuracy in BRVO images. This emphasized to develop a novel algorithm to effectively register the retinal images affected with BRVO.

BRVO images are often reported with endothelial vascular damage and neo vascularisation. The segmentation of blood vessels is tedious in such images due to the arterio-venous crossings. A modified local entropy based thresholding is experimented to separate the foreground and background pixels. The blood vessels are segmented after analyzing the length and orientation of these vascular structures. A directional finding algorithm is attempted to extract the blood vessels for further refined registration using binary particle swarm optimization technique.

5.3 PERFORMANCE OF BPSO BASED REGISTRATION

PSO is a global gradient less stochastic search method that suits for both continuous and discrete problems in optimization. Simple PSO involves the assigned particles to move in the search space with changes in their
position coordinates. The positions of the particles are updated on each iteration depending on the velocity to attain a local best position and global best position of the entire swarm. BRVO Retinal image registration using a directional finding algorithm comprises of crossover and fine neo vascularisations. These fine complex data have to be used as the search space in the maximization of the similarity metric. PSO can be slightly modified with a binary search space as binary particle swarm optimization which involves binarization of the moving coordinates in the search space. The BPSO is effective in retinal image registration as it does not require initial user specified orientation of the images. This technique proved improved accuracy when tested with all the three sets of images not less than 80%.

5.4 COMPARATIVE ANALYSIS OF PROPOSED METHODS

Figure 5.1 depicts a comparison to the average success rate for various registration algorithms proposed in this research and methods available in the literature for various sets of retinal images.

The motivation of this research is to detect the retinal occlusion by registering the retinal images obtained at different stages of pathological conditions. Hence a detailed analysis is undergone in all the proposed registration methods to evaluate the success rate in detecting the occlusion with various possible sets of retinal images. The images in the database are segregated into CRVO and BRVO images and all the proposed methods in this research work are tested with both types of images. The success rate of registration using various methods is shown in Table 5.3.
Figure 5.1  Average success rate for proposed registration methods

Table 5.3  Success rate for CRVO & BRVO image registration

<table>
<thead>
<tr>
<th>Type of RVO</th>
<th>Number of Images</th>
<th>MIREB with SA</th>
<th>MIREB with GA</th>
<th>RANSAC with GICP</th>
<th>BPSO-DF</th>
</tr>
</thead>
<tbody>
<tr>
<td>CRVO</td>
<td>47</td>
<td>40.86</td>
<td>41.56</td>
<td>88.56</td>
<td>80.1</td>
</tr>
<tr>
<td>BRVO</td>
<td>78</td>
<td>46.57</td>
<td>42.34</td>
<td>79.54</td>
<td>90.44</td>
</tr>
</tbody>
</table>

It is interpreted that CRVO images are effectively registered with RANSAC matching & Gradient ICP algorithm with an average success rate of 88.56%. The BRVO images are registered with a success rate of 90.44% by
using binary particle swarm optimization. The comparative success rate for all the proposed registration methods for CRVO and BRVO images is shown in Figure 5.2.

![Average success rate for CRVO and BRVO](image)

**Figure 5.2** Average success rate for CRVO & BRVO images

### 5.5 SUMMARY

Hence it can be summarized that the registration of retinal images involves various critical procedures and processing to aid the physician in early diagnosis of retinal occlusion. The retinal images affected by occlusion available from the database are preprocessed for noise removal with edges and vascular structures identified in prior. But the real time retinal images affected by occlusion obtained from the ophthalmologists report with a high degree of noise and non uniform illumination. Hence the registration needs a detailed study of the anatomical and pathological conditions of the affected retina. Two different approaches using RANSAC and BPSO based registration help the physician to diagnose CRVO and BRVO respectively.