Registration of Bimodal Retinal Images – improving modifications

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Abstract—**The proper optical disc segmentation in images provided by confocal laser scanning ophthalmoscope and by color fundus-camera is a necessary step in early glaucoma or arteriosclerosis detection. Fusing information from both modalities into a vector-valued image is expected to improve the segmentation reliability. The paper describes a registration of these images using optimization based on mutual information criterion function extended with gradient-image mutual information. The controlled random search (CRS) has been found more robust optimization routine than the simulated annealing (SA) while tested on a set of 174 image pairs. Finally, the multi-resolution algorithm for bimodal retinal image registration achieving the success-rate of 94% is proposed.**

Keywords—**image registration, ophthalmologic image processing, retina, mutual information, optimization, controlled random search, simulated annealing, simplex**

I. Introduction

To improve early glaucoma detection and its progression monitoring, the Heidelberg Retina Tomograph (HRT) is used. The HRT is a confocal laser scanning opthalmoscope, which provides 3D image data of the human retina, from which the integral intensity image is derived [6]. The standard fundus-camera provides different information; the color photographs are used for vessel segmentation and for computing arterio-venous diameter ratio, which is important for early detection of arteriosclerosis and diabetic retinopathy. In both cases, it is important to detect the border of the optic nerve head (optic disc) correctly. It is expected, that fusing information from both modalities to a vector-valued image, rather than analyzing each modality separately, may produce more robust segmentation. This paper describes an improved method of geometrically transforming one image to fit the other so that they may be fused into a vector image.

II. Methodology

Registration by maximization of mutual information

Registering two images means to find the transformation aligning the contents of the images. There are more possibilities to do that [10], one of them is to maximize a similarity criterion [6]. It can be formalized as

$$\alpha_0 = \arg\left\{\min_{\alpha} C\left(R, T_\alpha\left(F\right)\right)\right\}, \tag{1}$$

where R is the reference image and F is the floating image to be registered, which is transformed by T_α to coordinates of the reference image. The registration quality, corresponding to the transform T_α, is evaluated by the criterion C. The optimal transformation $T_{\alpha 0}$ transforms the floating image F into the image $T_{\alpha 0}(F)$, which contains maximal possible information about the reference image R. In [6], it has been shown that mutual information is a robust measure of similarity, but it fails in some types of used ophthalmic images due to false global extremes. Mutual information I of images R and $T_\alpha(F)$ can be computed as:

$$I\left(R, T_\alpha\left(F\right)\right) = H\left(R\right) + H\left(T_\alpha\left(F\right)\right) - H\left(R, T_\alpha\left(F\right)\right), \tag{2}$$

where $H(R)$ and $H(B)$ denote the marginal entropies of the reference image R respectively transformed floating image $T_\alpha(F)$, and $H(R,\ T_\alpha(F))$ denotes their joint entropy. These entropies can be evaluated using joint histograms of the images [3]. To improve the quality of the criterion, particularly to avoid the false global extremes, gradient-image mutual information defined in (5) is incorporated in our optimization criterion. Derived gradient-magnitude images are created from both reference image R and transformed floating image F by convolving them with appropriate first derivatives of a Gaussian kernel. Gradient-magnitude of an image A is defined as

$$\left|\nabla A\right| = \sqrt{\left(h_x * A\right)^2 + \left(h_y * A\right)^2}, \tag{3}$$

where * is the convolution operation and h_x, and h_y are the appropriate derivatives of the Gausian kernel $h(x,y)$:

$$h\left(x, y\right) = \left(\frac{1}{\sqrt{2\pi\sigma}} e^{-\left(x^2/2\sigma^2\right)}\right) \cdot \left(\frac{1}{\sqrt{2\pi\sigma}} e^{-\left(y^2/2\sigma^2\right)}\right). \tag{4}$$

Then the gradient-image mutual information $GI(R,T_\alpha(F))$ of the reference image R and the transformed floating image $T_\alpha(F)$ is evaluated as:

$$\begin{aligned} GI\left(R, T_\alpha\left(F\right)\right) = {} & H\left(\left|\nabla R\right|\right) + H\left(\left|\nabla T_\alpha\left(F\right)\right|\right) \\ & - H\left(\left|\nabla R\right|, \left|\nabla T_\alpha\left(F\right)\right|\right), \end{aligned} \tag{5}$$

The final optimization criterion $Y(R,T_\alpha(F))$ is defined as

$$Y\left(R, T_\alpha\left(F\right)\right) = I\left(R, T_\alpha\left(F\right)\right) \cdot GI\left(R, T_\alpha\left(F\right)\right)\ . \tag{6}$$

The registration mentioned above consists in searching for a proper vector α of parameters in multidimensional space. Due to many local extremes of the similarity criterion, the usually used Powell's optimization method is not suitable for the case of multimodal retinal images. Therefore, the more robust simulated annealing algorithm and the controlled random search algorithm were tested.

Simulated annealing

Simulated annealing (SA) is a technique to find a solution to an optimization problem by trying random variations of the current estimate. A worse variation may be accepted as the new solution with a probability that decreases as the computation proceeds. The slower the cooling schedule, or rate of decrease, the more likely the algorithm is to find an optimal or near-optimum solution. SA tries to avoid local minima by jumping out of them early in the computation. Towards the end of the computation, when the probability of accepting a worse solution is nearly zero, this simply seeks the bottom of the local minimum. The chance of getting a good solution can be controlled by slowing down the cooling schedule. The slower the cooling, the higher the chance of finding the optimum solution but the longer the run time. Thus effective use of this technique depends on finding a cooling schedule that yields good enough solutions without taking too much time. The algorithm can be formalized as on the Fig 1; for a more detailed description see [2], [6].

1. Let $\mathbf{x}_0 \in X$ be a given initial point, $z_0 = \{\mathbf{x}_0\}$, $k = 0$, where X is the search space.
2. Generate a point $\mathbf{y}_{k+1}$ from a next candidate distribution $D(z_k)$.
3. Sample a uniform random number $p \in [0,1]$ and set

$$\mathbf{x}_{k+1} = \begin{cases} \mathbf{y}_{h+1} & \text{if } p \le A(\mathbf{x}_k, \mathbf{y}_{k+1}, t_k) \\ \mathbf{x}_k & \text{otherwise} \end{cases}$$

   where A is the acceptance function, $A \in [0,1]$,
   t_k if the parameter called temparature in current iteration k.
4. Set $z_{k+1} = z_k \cup \{\mathbf{y}_{k+1}\}$, the set z_k contains all the information collected up to the interation k.
5. Set $t_k = U(z_{k+1})$, where U is called cooling schedule.
6. Check a stopping criterion; if it fails, set $k = k+1$ and continue with step 2.

Fig. 1. Simulated annealing algorithm (SA)

Controlled random search

Controlled random search (CRS) is a direct search technique and a pure heuristics. It is a kind of contraction process where an initial sample set of N points is iteratively contracted by replacing the worst point with a better one. The replacement is controlled by appropriate heuristics h. In the original version of CRS [8], a simplex is formed from a subset of $n+1$ points, where n is the dimension of the optimization problem. One of the points is reflected in the centroid of the remaining points to obtain the new trial point. The algorithm is described on the Fig. 2.

generate population $P=\{\mathbf{x}_n\}$, i.e. N random points from the search space X.
repeat
find $\boldsymbol{x}_{\max}$ from P so that $f(\mathbf{x}_{\max}) \ge f(\mathbf{x})$, for $\forall\ \boldsymbol{x} \in P$
  repeat
    $\boldsymbol{y} \leftarrow h(P)$, where $\boldsymbol{y}$ is from the search space.
  until $f(\mathbf{y}) < f(\mathbf{x}_{\max})$
  $\mathbf{x} \leftarrow \mathbf{y}$.
until termination condition

Fig. 2. Controlled random search algorithm (CRS)

We used a modification of this algorithm using alternating heuristics h. This algorithm simply randomly alternates (with uniform probability) k heuristics with constant probability $1/k$ of the selection of the i-th heuristic. For the more detailed description see [9].

III. RESULTS

Implemented registration method

The rough detection of the optic disc position in both to-be-registered images is used. It improves the algorithm accuracy and lessens computational demands. Then either of the SA or the CRS algorithms, in combination with the multiresolution (pyramidal) optimization approach, is applied. First pyramid layer is used for finding the optimal translational parameters using four-times subsampled images. The results of the rough detection of the optic disc position are used to set the initial point of the search algorithm. Second pyramid layer is proposed to determine all parameters of the affine transform using four-times subsampled images and the results of the previous step. Finally, all parameters are refined using the full resolution image data by Nealder-Mead method in the third pyramid layer. The parameters found in the second layer are supposed to be so close to the optimal parameters that the criterion can be considered as the quadratic form.

Experimental results

The proposed algorithm was tested on a set of 174 images of human retina acquired by means of the HRT and the color fundus-camera. First, the success-rate of the rough detection of the optic disc positions was tested. Detection was considered successful if the detected point lays inside the optic disc. The success-rate of the detection of the optical disc in the Canon image was 97.1% and in the HRT image 99.4%. There is no golden standard available, so that accuracy of all the algorithms was judged by a human observer. For this purpose, HRT image was combined with the edges from the Canon image (see Fig. 3). Five runs over the complete image set were done with randomly initiated seed of the random generator. An image-pair was considered properly registered if there was no error in all five runs. Misregistered images were counted, then the rate of registration success was computed and was 86.7 % using SA and 94.2% using CRS. When only good quality input images were considered, the success-rate rose to 91% for SA and 96,5% for CRS (see Table I). Due to inaccessibility of the golden standard we cannot quantify the obtainable precision, thus we calculate the variance of the parameters in five runs for each pyramid layer (see Fig. 3 or Table II). Only properly registered image pairs were taken into account. Consistency of the proposed algorithm was tested on a randomly selected image pair by repeating the randomly diversified registration one hundred times. Images were properly registered in all those runs.

IV. DISCUSSION

In some cases, we found that the mutual information had global extreme out off the point of subjective registration. Therefore we incorporated gradient-image mutual information into our criterion (6).

There are several problems with registration of this type of ophthalmic images: a multimodal character of input data, very broad parameter space (see table III) and the dimensionality of the optimization problem (at least six parameters of the used affine transformation). Each of these features makes the optimization difficult and it is necessary to use robust optimization method to determine the globally optimal transformation parameters. Two global optimization algorithms were tried. The SA algorithm was very difficult to set properly; particularly to harmonize decreasing of the global temperature and the range of the parameter generation in each iteration. On the other hand, the CRS algorithm with alternating heuristics was simple to set and it is more successful than SA as it was shown in the Table I. Hence, the CRS algorithm was finally embedded into our multiresolution registration algorithm.

The first optimization pyramid layer guesses the coarse translational parameters. This is not difficult as there are only two parameters. The second layer of the pyramid is crucial. The precision of the optimization is determined mainly by the size of the population P (see Fig. 2) and by the limitation of the maximum number of criterion evaluations.

TABLE I
RATE OF SUCCESS OF THE PROPOSED ALGORITHM USING THE CRS OR THE SA OPTIMIZATION.

Metod	CRS	SA
Total number of images	174	174
Wrong rough optic disc detection (err. #0)	4	5
Unsubstantiated misregistration (err. #1)	2	10
Low quality input (err. #2)	4	8
Rate of success [%] (all errors)	94,25	86,78
Rate of success [%] (errors #0, #1)	96,47	90,96
Rate of success [%] (errors #1)	98,80	93,79

TABLE II
THE VARIANCE FOR IMAGE PAIRS PROPERLY REGISTERED IN 5 RUNS USING THE PROPOSED ALGORITHM WITH THE CRS OPTIMIZATION ROUTINE. TIME TAKEN AND NUMBER OF CRITERION EVALUATIONS ARE AVERAGES FOR COMPLETE TESTING SET.

	Variance for 5 x 160 runs							
	Translation		Scale		Shear			
Layer	x [px]	y [px]	x [%]	y [%]	x [10^{-2}]	y [10^{-2}]	Time Taken (mins)	MI eval.
1	1.24	2.06					0:22	640
2	0.57	0.32	0.26	0.16	0.17	0.16	3:40	6400
3	0.57	0.32	0.25	0.16	0.17	0.14	1:02	90

We have made a compromise between the algorithm precision and its speed and set the maximum criterion evaluations to 6400. The precision obtainable by these settings is shown in the Table II or Fig. 3 and is sufficient for subsequent processing, i.e. optical disc detection.

The last layer serves only for the refining the parameters found in the previous layer to full resolution. The Nealder-Mead simplex method is used for optimization in this layer because of the assumption of being nearby the global extreme.

V. CONCLUSION

The mutual information in combination with gradient-image mutual information was found the only suitable similarity criterion for finding optimal parameters of the affine transform and thus to register the multi-modal ophthalmic images. Jitter sampling, histogram blurring and, particularly, lowering the number of intensity bins were used to prevent interpolating artifacts. Unfortunately, the occurrence of local extremes of the mutual information makes conventional optimization algorithms ineffective in a wider range of parameters. Therefore, the more robust optimization techniques, simulated annealing (SA) and controlled random search (CRS) were tried. The CRS algorithm was found more robust and hence it was incorporated into the proposed multiresolution registration algorithm. The success-rate of the method was tested on the training set contained 174 image pairs, 94.25% image of them were successfully registered in spite of very varying image quality. It seems necessary to generalize the approach using elastic registration, at least for some images. This remains open for future research.

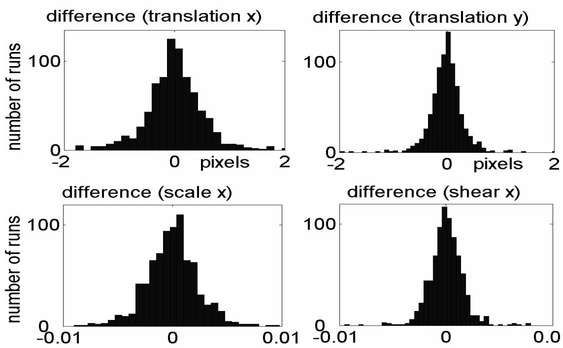

Fig. 3. The distribution of differences among parameter values found using search and its mean value.

TABLE III
BOUNDARY PARAMETER VALUES OBTAINED DURING REGISTRATION OF THE TESTING IMAGE SET (160 PROPERLY REGISTERED IMAGE PAIRS)

	Translation		Scale		Shear	
Bound	x [px]	y [px]	x [%]	y [%]	x	y
Upper	243	252	110	104	0,19	0,11
Lower	-311	-57	92	89	-0,11	- 0,13

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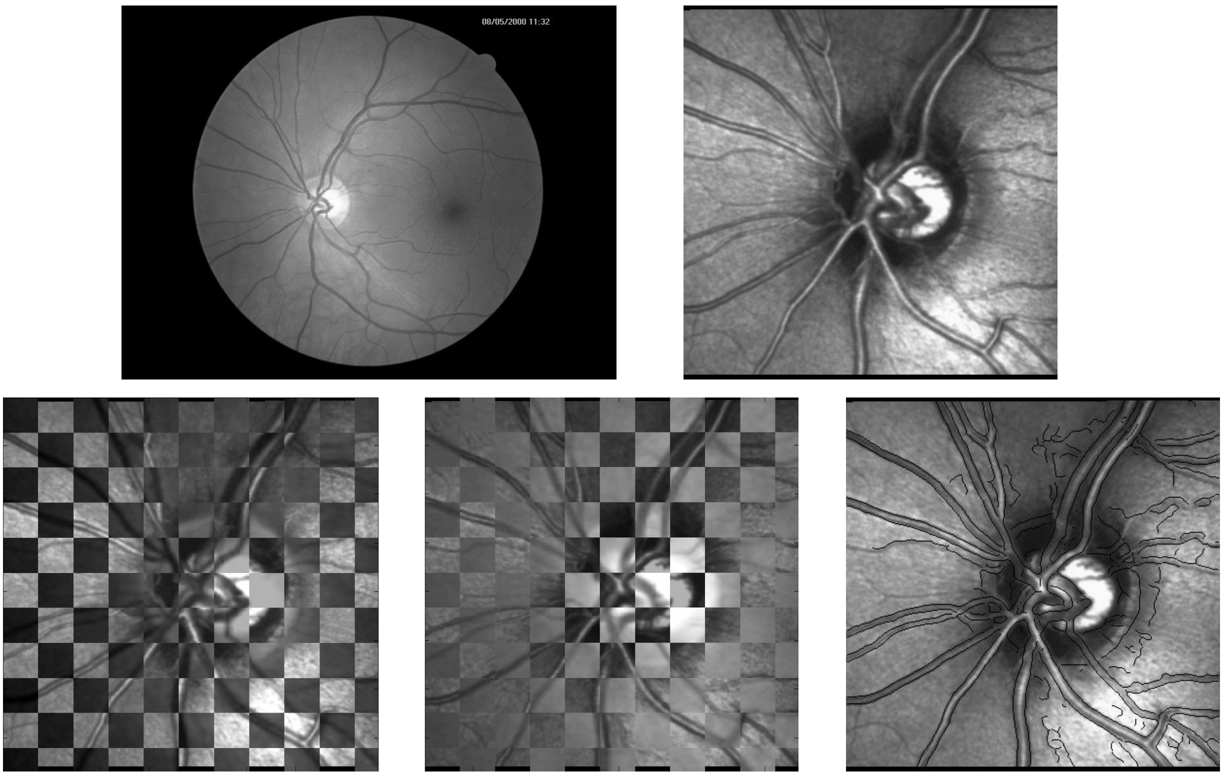

Fig. 3. Top left: image from fundus camera. Top right: integral intensity image from the confocal laser tomograf (HRT). Bottom left and middle: Mosaic created from both registered images (alternating fields from the fundus camera and the laser tomography and vice versa). Bottom right: HRT image with superimposed edges obtained from registered fundus camera image using Canny edge detector - visual test of proper image registration