MUTUAL INFORMATION BASED REGISTRATION OF RETINAL IMAGES

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ABSTRACT

Registration of multimodal images of retina is essential for correct diagnosis of the optic nerve head and retina. For reliable vessel segmentation, it is also important to use information from both, color photographs and Heidelberg Retina Tomograph (HRT) scans. Mutual information was tested as a coincidence measure and has proven functional and reliable. This paper proposed a robust method for finding the correct transformation parameters with specificity about 93 %.

1 INTRODUCTION

To improve early glaucoma detection and progression monitoring, the Heidelberg Retina Tomograph (HRT) is used. The HRT is a confocal laser scanning system, which provides 3D image data of the human retina composed of grayscale image slices in different focus planes. Collecting the sums of voxel intensities across all slices into 2D matrix provides sc. intensity image. The standard color photographs provide different information; they are used for vessel segmentation and for computing of sc. A/V 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. After that, the vessel segmentation can be done in the color photograph, and HRT scans can be used for computing parameters of optic nerve head. Nowadays, physicians segment the optic disc manually and thus the results vary with different observers. The goal is to segment the optic disc automatically with a reasonable degree of robustness. Chrastek [2] uses Hough transform and adaptive anchored contours for this purpose. Rather than analyze the each modality separately, we found, that to produce a robust segmentation, fusing information from both modalities to a vector-valued image is helpful. This bi-modal vector-valued image with 4D pixels is composed of three RGB components of the color image and one value of the intensity image and it's used for better segmentation. Before combining both images, they must be correctly aligned. This paper describes the robust method for transforming the one image to fit the other one. This method was done by fully automatic finding parameters of the affine transform.

2 METHODS

2.1 REGISTRATION

The registration can be defined as searching for the best geometric transform, which describes the relationship between the reference image and the registered image [2]. The used affine transform T is supposed to depend on a vector parameter α, encompassing shift, rotation, scale and skew. The parameter is found by optimization,

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

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, is evaluated by function C. $T_{\alpha 0}$ is then the optimal registering transform with a respect to the criterion. The expected geometric distortion of images is a combination of displacement, rotation, scaling and skew. As it has been proven in [3], the affine transform is sufficient for compensation of such a distortion.

2.2 OPTIMIZATION CRITERION

Due to differences in properties of the used imaging modalities, commonly used similarity (or registration) criteria fail. Thus we have to apply a measure that can cope with substantially differing contrast mechanisms of corresponding features in both images. It has been shown, e.g. [4], that the mutual information is a suitable measure. According to the information theory, the degree of the dependency between random variables (images) A and B is given by their mutual information I(A,B).

$$I(A,B) = H(A) + H(B) - H(A,B),$$

where H(A) and H(B) denote the marginal entropies of A respectively B, and H(A,B) denotes their joint entropy. These entropies can be evaluated using joint histograms of images as defined in [4],

2.3 DETERMINATION OF TRANSFORMATION PARAMETERS

The fully automated approach consists in searching for a proper set of parameters in multidimensional parameter space. Mutual information is used as the matching criterion. Due to computational demands it seems wise to use some kind of pyramid processing. In this case, images are first sub-sampled and parameters are computed only roughly; after that, searching is done again, under finer sampling, with rough parameters used as initial values. Due to presence of many local extremes of the function of mutual information, the usually used Powell's optimization method is unsuitable for the case of multimodal retinal images. Therefore the more robust simulated annealing algorithm was performed.

The method of simulated annealing (SA) is a technique that is generally suitable for optimization problems of large scale, especially ones where a desired global extreme is hidden among many, poorer, local extreme. The simulated annealing method combines the use of three functions: a generation function, an acceptance function and an annealing schedule. The SA algorithm generates coordinates of the new attempt in the parameter space in each iteration and after that, the acceptance function decides if the new parameter values become current values or if - to allow escape from local minimums - it would be discarded. The acceptance function is controlled by the parameter called *temperature* (see later).

The decision process can be formalized as follows:

$$x_{k+1} = \begin{cases} y_{k+1} & \text{if } \mathrm{p} \le \mathrm{A}(\mathrm{x}_{\mathrm{k}}, y_{k+1}, t_k) \\ x_k & \text{otherwise} \end{cases},$$

where x_k is the actual value, y_{k+1} is the generated value, $p \in [0,1]$ is a random number with normal distribution, t_k is the actual temperature and x_{k+1} is the value, which will be used in the next iteration. A is the acceptance function; the sc. Metropolis function has been used:

$$A(x, y, t) = \min\left\{1, \exp\left\{-\frac{C(y) - C(x)}{t_k}\right\}\right\},$$

This function always accepts the steps leading to a lower function value, but if the algorithm locks in a false local minimum, it allows steps leading towards higher (worse) value with probability based on the temperature and the degree of deterioration. During iterations, temperature decreases as given by the annealing schedule as

$$t_{k+1} = \frac{t_k}{[\ln(k)]^g}$$

3 EXPERIMENTAL RESULTS

3.1 MUTUAL INFORMATION COMPUTATION, INTERPOLATION ARTEFACTS

The process of computation mutual-information can be divided in three steps. First, floating image is transformed and superposed with reference one. Then the joint histogram (JH) is constructed from the overlap region of these two images and finally a match metric is determined from the joint histogram. Interpolation algorithms are necessary needed to estimate the pixel intensities at nonrigid positions, whenever the pixel grids of both images are not in exact alignment.

We have tried several methods for constructing JH, beginning with the simplest nearest-neighbor (NN) interpolation, over bilinear (B) interpolation as an intermediate step to the partial volume (PV) interpolation. The NN and bilinear interpolation are used to interpolate the resulting image and after that joint histogram is computed from the interpolated image. PV interpolation updates the values in the joint histogram directly by finding a group of the nearest pixels rather than interpolating the images [1]. Unfortunately, the interpolation induces a pattern of local extremes in the registration function, caused by the imperfect interpolation of gray levels from the neighbor grid points. NN interpolation produces stairs-like artifacts, which occur at every half-pixel step, coinciding with discontinuities of the interpolation kernel. The bilinear interpolation produces arch artifacts, which are accentuated with increasing number of intensity bins. The partial volume interpolation induces inverted arches pattern of the MI cost-function.

To overcome this problem, a combination of three approaches was proposed - nearest neighbor interpolation with jitter sampling, histogram blurring and number of intesity bins decreasing. By jitter sampling, a small random number, uniformly distributed in interval [-0.5; +0.5], is added to coordinates of every pixel to be transformed and only afterwards the NN interpolation is done. Then the created joint histogram is blurred by convolving with a low-pass Gaussian filter with standard deviation 0.5 and size 4x4. It was found, that interpolating artifacts are less sharp using less number of intensity bins. Experimentally, it was found, that the proposed optimization algorithm works best with 20 intensity bins.

3.2 PROPOSED REGISTRATION ALGORITHM

Function of MI cannot be well approximated by a quadratic form, as required by Powell's and Nealder-Mead's optimization procedures, so that simple approaches for optimization of multi-parameter function fail. Thus the only suitable method of the tested ones is the simulated annealing. Parameter space is large and its searching is thus computationally very demanding. It is then necessary to use the pyramid sampling.

The rough detection of optic discs in both to-be-registered images is used. It improves the algorithm accuracy and lessens computational demands. Then the SA algorithm in combination with the multiresolution optimization approach are applied. First, optimal translational parameters are found using four times subsampled images and results of the rough detection of optic discs. Then all parameters of the affine transform are found using four times subsampled images and results of the previous step. Finally all parameters are refined in the full resolution images.

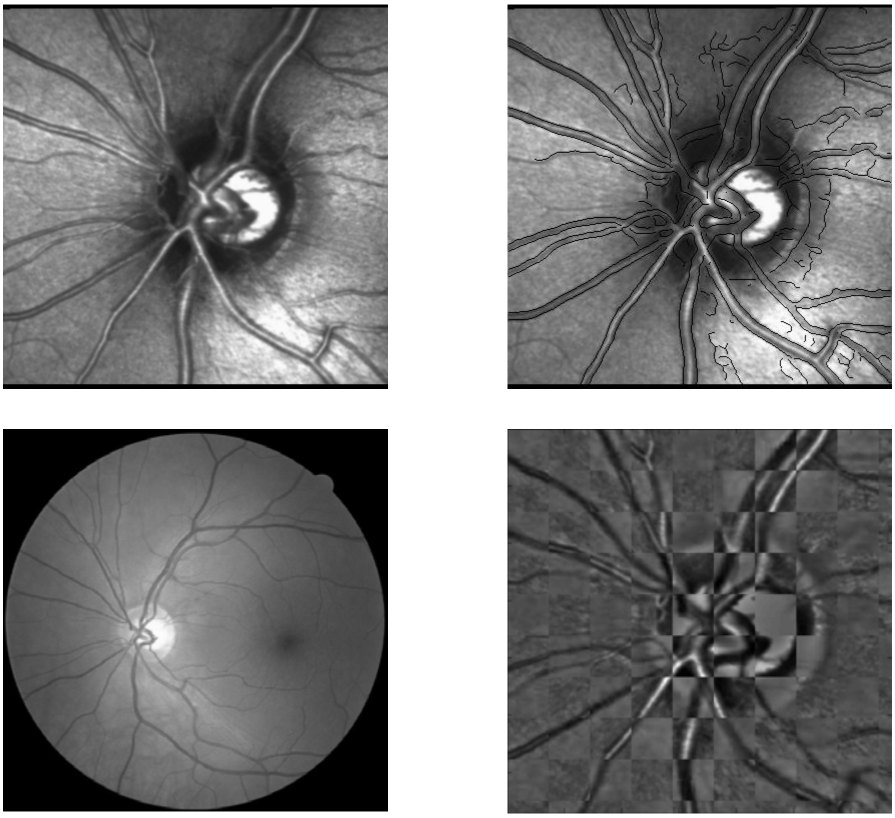

Fig. 1: ***Top left***: *image from the confocal laser tomgraf (HRT),* ***Bottom left***: *image from fundus camera.* ***Top right***: *HRT image with superimposed edges obtained from fundus camera image using Canny edge detector.* ***Bottom right***: *Mosaic created from both registered images (alternating fields from the fundus camera and the laser tomograph).*

3.3 RESULTS AND DISCUSSION

The proposed algorithm was tested on a set of 174 images of human retina acquired from the HRT and the Canon color camera. The quality of these images was very different; many of them were blurred or corrupted by very bad illumination conditions or by some artifacts produced by incorrect acquisition. The algorithm was tested on all this images. First the specificity of the rough optic discs detection was tested. The detection was considered successful if the detected point laid inside the optic disc. The specificity of the detection of the optical disc in the Canon image was 97.1% and in the HRT image 99.4%. There was no gold standard so accuracy of all algorithm was judged by a human observer. For this purpose, a new HRT image containing edges from Canon image was made. Edges were detected by Canny edge detector. Five runs over the whole image set were done. All misregistered images in all runs were counted and then the rate of success was computed. The specificity of the registration was 89.1 %. When the very bad quality images were not considered, the specificity was 93%.

4 CONCLUSIONS

The robust approach for the registration of multimodal ophtalmologic images have been presented. In particular, mutual information was optimized for finding parameters of the affine transform. Jitter sampling, histogram blurring and particularly number of intesity bins decreasing were used to prevent interpolating artifacts. The simulated annealing optimization algorithm was performed together with the pyramid sub-sampling to speed it up. The method has successfully registered 93% of accessible images in spite of very different quality of them. There seems to be necessary to use an elastic registration for some images. Thus, it remains open for future analysis.

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