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Image Registration by the Extended Evolutionary Self-Organizing Map

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Abstract. The Evolutionary Self-Organizing Map (EvSOM) is a recently proposed robust approach for topographic map formation that is based on evolutionary algorithms. In this work, a variant of EvSOM is proposed in order to fully exploit the neighborhood preservation property of the topographic maps induced by it when dealing with the image registration (IR) problem. In particular, the novel EvSOM is adopted here with the assumption that the relationship between the reference image and the free image can be approximated by an affine transformation. Preliminary experiments with black & white retinal blood vessel images are discussed, comparing the performance of EvSOM with that of two well-known IR methods, namely, iterative closest point and template matching. Overall, the results confirm the potentials of the extended EvSOM in this new application scenario.

1 Introduction

In a nutshell, image registration (IR) is the process of matching all or some interest points pertaining to two images of the same scene taken at different times, possibly from different sensors, and from different viewpoints. As a consequence, these images may be subject to relative translation, rotation, scale, and other geometric transformations, demanding the development of spatial and intensity alignment procedures [6]. Applications of IR can be easily found in areas such as remote sensing [8], medical image analysis [5, 3], and computer vision [4].

When coping specifically with feature-based (i.e. surface and intensity) registration, one faces the problem of finding the optimum or a good suboptimal spatial transformation (mapping) between the two sets of image features. This is a challeging task to pursue mainly for three reasons. First, due to the noise that may arise from the processes of image acquisition and feature extraction. The presence of noise entails that the resulting feature points cannot be exactly matched. Second, due to the existence of outliers: Many point features may exist in one point-set that have no corresponding points (homologies) in the other point-set, and, so, need to be rejected during the matching process. Finally, the geometric transformations may need to incorporate high dimensional non-rigid mappings in order to account for deformations of the point-sets. To properly address all these issues, a general point feature registration algorithm capable of simultaneously finding correspondences between the point-sets, rejecting outliers, and yielding a good non-rigid transformation from one point-set to the other is much needed.

In the course of image matching, notably with respect to deformable structures, topology preservation usually appears as a strong and global constraint, ensuring that connected structures remain connected and that the neighborhood relationship between structures is maintained. It also prevents the disappearance of existing structures or the appearance of novel ones. These properties are related to the continuity and inversibility of the deformation itself. By enforcing this constraint, the space of possible solutions is restricted to deformations satisfying the real-world property of matter [7].

In this paper, following the steps of Coppini et al. [1] and Markakia et al. [2], we deal with the problem of matching medical images by exploiting the neighborhood preservation property of topographic maps (TM). More precisely, we investigate the potentials of applying a recently proposed approach, the Evolutionary Self-Organizing Map (EvSOM) [10, 11], for this purpose. EvSOM is an evolutionary algorithm for generating TM that has proved to be strongly resilient to outliers, less sensitive to control parameter selection, and less susceptible to the effects of multimodality and local optima.

Originally, topology preservation in EvSOM has been induced by resorting to the Pearson correlation of the distances between neighboring prototypes in the input space and the distances between their coordinates in the output array [11]. In this work, to cope specifically with the IR problem, a new version of EvSOM is put forward whereby a measure of matching between a reference image (I_r) and a free image (I_f) is adopted as fitness function. Preliminary experiments with black & white retinal blood vessel images are discussed, comparing the performance of the novel EvSOM with that of two well-known IR methods, namely, iterative closest point (ICP) [3] and template matching (TEM) [13].

The remainder of the paper is organized as follows. In Section 2, we outline the EvSOM algorithm and its adaptation to tackle the IR problem. In Section 3, we characterize the dataset used, present the results achieved, and discuss them accordingly. Section 4 concludes the paper.

2 The Evolutionary Self-Organizing Map (EvSOM)

Assume a dataset D having L data samples residing in an input space of dimension P, that is, $D = \{\mathbf{x}_l \in \mathbb{R}^P, l = 1, \ldots, P\}$. As an evolutionary optimization approach, the main goal of EvSOM is to locate the map that best characterizes D in terms of its topological properties. In order to do that, a population of TM is encoded into individuals that are evolved across generations through the application of genetic and selection operators. Each evolved map is arranged as a grid of N neurons, each located in a fixed position in the output array and associated with a vector of weights, $\mathbf{w}_j \in \mathbb{R}^P$, $j = 1, \ldots, N$.

A chief component of EvSOM is the special fitness function adopted so as to provide a proper balance between the levels of quantization error and topological preservation. This fitness function is thus a linear combination of the Quantization Error (QE) and the Pearson Correlation Coefficient (PCC) indices:

$$Fitness(\widetilde{\mathbf{W}}) = \alpha \cdot PCC(\widetilde{\mathbf{W}}) - \beta \cdot QE(\widetilde{\mathbf{W}}), \tag{1}$$

where $\widetilde{\mathbf{W}} = \{\mathbf{w}_1, ..., \mathbf{w}_N\}$ denotes the whole set of weight vectors, and the parameters $\alpha, \beta \in [0, 10]$ weigh the relative importance of the indices with respect to each other. The QE index assesses how good is the map in providing a compact representation of the original data set. Mathematically, it can be defined as:

$$QE(\widetilde{\mathbf{W}}) = \frac{1}{L} \sum_{l=1}^{L} \left\| \mathbf{x}_l - \mathbf{w}_{i(\mathbf{x}_l)} \right\|, \tag{2}$$

where $\mathbf{w}_i$ is the weight vector of the winning neuron and $i(\mathbf{x}_l) = \arg\min_{\forall j}\{\|\mathbf{x}_l - \mathbf{w}_j\|\}$. The PCC index is the cross-correlation between the distances $\{d(\mathbf{r}_m, \mathbf{r}_n)\}$ and $\{d(\mathbf{w}_m, \mathbf{w}_n)\}$, where $(\mathbf{r}_m, \mathbf{r}_n)$ are the coordinates of pairs of neurons in the output array and $(\mathbf{w}_m, \mathbf{w}_n)$ are the corresponding pairs of weight vectors:

$$PCC(\widetilde{\mathbf{W}}) = \frac{\sum_{m=1}^{N} \sum_{n=1}^{N} d(\mathbf{r}_m, \mathbf{r}_n) d(\mathbf{w}_m, \mathbf{w}_n)}{(N-1)\, S_r S_w}, \tag{3}$$

where S_r and S_w are the standard deviations of the distances $d(\mathbf{r}_m, \mathbf{r}_n)$ and $d(\mathbf{w}_m, \mathbf{w}_n)$, respectively. It is worth noting that PCC is an index of the type *the larger, the better*, while QE is of the type *the lesser, the better.*

2.1 Extended EvSOM to cope with the IR problem

Here, a variant of EvSOM is introduced as an intensity based method for image registration. In particular, we have assumed that the relationship between I_r and I_f can be well approximated by an affine transformation. Anyway, a good property of the method is that it requires the extraction of interest points (bifurcations) from only one image.

The first step is to define the EvSOM topology. For this purpose, a set of interest points from I_r and their neighborhoods (a.k.a. templates) are considered as the neurons in the output grid. To each neuron, a weight vector is assigned holding the parameters of a local transformation. Each transformation provides the mapping between an interest point in the reference image and its corresponding one in the second image. The parameters of the local transformations are calculated by means of an iterative optimization procedure. Details about it are given in [1]. The update of the transformation parameters aims at optimizing the matching between templates, centered at the points of the reference image, and their transformed versions at the free image.

In order to evaluate the degree of similarity between regions of I_r and I_f, a measure of matching (MoM) between the two images is required. The MoM could be any criterion quantifying the similarity between the two images, such as the root-mean-square error (RMSE) [2], the mutual information (MI) [9], or the squared correlation coefficient (SCC) [3]. In our experiments, the sum of the absolute differences (SAD) [7] has been used:

$$SAD = \sum_i \sum_j |I_r(i,j) - I_f(i,j)|, \tag{4}$$

where $I_r(i,j)$ and $I_f(i,j)$ denote, respectively, the intensities of gray levels in the reference and free images. Note that this index is of the type *the larger, the better*. So, after embedding it into the EvSOM fitness function, the latter now becomes:

$$Fitness(\widetilde{\mathbf{W}}) = \alpha \cdot PCC(\widetilde{\mathbf{W}}) + \beta \cdot MoM(\widetilde{\mathbf{W}}). \tag{5}$$

In short, the goal of the extended EvSOM algorithm is to iteratively determine the parameters of a local affine transformation that maps each interest point of I_r to its corresponding point in I_f. The mapping is determined by jointly optimizing the MoM index (SAD, in this paper) and the PCC index, whose role here is to measure the correlation between neighborhood interest points from the two images.

3 Computer Simulations and Discussion

All images were obtained from the DRIVE project repository [12]. Interest points were selected manually and the templates centered at these points comprise subimage grids of 21×21 pixels. Sixteen black-and-white images have been used and for each image five runs with different interest points were performed. So, the results conveyed in Table 1 are the average values of $16 \times 5 = 80$ runs. For each run, only five interest points were selected, a small number compared to the experiments reported in most of the previous related studies [1, 2].

Figure 1 shows a typical qualitative result achieved with the EvSOM-IR procedure while Table 1 brings quantitative results. To finally assess the quality of the whole IR process, the Normalized Cross Correlation (NCC) coefficient has been adopted, which is defined as [13]:

$$NCC = \frac{\sum_{i,j}(I_{ref}(i,j) - \bar{I}_{ref})(I_{reg}(i,j) - \bar{I}_{reg})}{\sqrt{\sum_{i,j}(I_{ref}(i,j) - \bar{I}_{ref})}\sqrt{\sum_{i,j}(I_{reg}(i,j) - \bar{I}_{reg})}}, \tag{6}$$

where $\bar{I}_{ref}$ and $\bar{I}_{reg}$ are, respectively, the average intensities of gray levels in the reference and registered images.

From Table 1, one can easily note that, for the experiments carried out in this paper, the proposed EvSOM-IR approach is consistently better than ICP, which is, in turn, consistently better than the standard TEM approach. In this table, NCC' stands for NCC prior to registration and s is the scale factor.

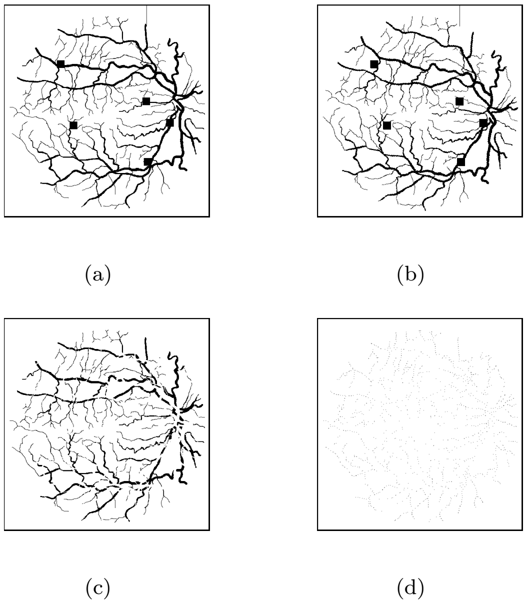

Fig. 1: Image registration process through EvSOM: (a) I_r with the five templates; (b) I_f obtained from I_r by an eight-degree rotation; (c) difference between I_r and I_f; and (d) difference between I_r and the EvSOM-registered image.

Table 1: Image registration results for EvSOM, ICP, and TEM methods.

Translation							
bx (pixels)	-12	-8	-4	0	4	8	12
NCC'	.738	.844	.912	1.000	.912	.844	.738
NCC(EvSOM)	.998	.999	.998	1.000	.998	.999	.997
NCC(TEM)	.988	.991	.996	1.000	.995	.990	.990
NCC(ICP)	.993	.996	.998	1.000	.999	.996	.992
Rotation							
θ (degrees)	-12	-8	-4	0	4	8	12
NCC'	.795	.838	.911	1.000	.911	.838	.795
NCC(EvSOM)	.983	.988	.992	1.000	.991	.986	.984
NCC(TEM)	.953	.973	.982	1.000	.989	.967	.955
NCC(ICP)	.964	.977	.992	1.000	.990	.976	.964
Scale							
s (factor)	.80	.85	.90	.95	1.0	1.05	1.10
NCC'	.580	.676	.742	.825	1.000	.828	.745
NCC(EvSOM)	.925	.961	.975	.985	1.000	.982	.974
NCC(TEM)	.904	.934	.965	.979	1.000	.983	.977
NCC(ICP)	.921	.956	.969	.985	1.000	.978	.957

4 Conclusion

The Evolutionary Self-Organizing Map algorithm (EvSOM) [10, 11] was extended here to handle the image registration problem and its accuracy performance was contrasted with that exhibited by two well-known algorithms, namely, template matching and iterative closest point. The results obtained from experiments conducted over a sample of images taken from the DRIVE repository [12] evidence superior performance of EvSOM for the majority of image pairs, as measured by the normalized cross-correlation coefficient.

As ongoing work, we are conducting novel experiments with gray-level images in order to compare the performance of EvSOM-based IR with that achieved with the variants of the Kohonen self-organizing map proposed in [1] and [2].

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