A self-organizing elastic map to measure the contour of skin pressure ulcers in digital images

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Abstract.

1 Introduction

The prevention, care and treatment of pressure ulcer pathology involve a high cost for sanitary system and imply important consequences for the health of the population. The progress of wound healing and the effect of clinical treatments can be evaluated partly by measuring the area of the wound. Starting from color digital images of pressure ulcers, traditional digital processing methods [3] for image segmentation —as boundary detection, edge linking, thresholding, region-based or morphological segmentation— do not reach concluding results and suffer from a high sensitivity to the initial parameter set. This is due to the intrinsic nature of this problem: pressure ulcer images are usually taken in not controlled environments and the nature of these wounds gives images of complicated colorations and vague boundaries where traditional algorithm confuse.

On the other hand, measurements taken via manually methods, such as using computer pointing devices to outline the ulcer boundary on the image, suffer from important variations due to differences in manual deftness or dissimilar opinions among observers. Finally, authomatic methods, as active contour modeling for adaptively regularize the boundary of the wound according to local conditions in the image, can give better results than manual methods [6], but fail to produce acceptable results when a portion of the wound boundary is vague, there are dark spots near to the boundary or the wound shape has narrow projections [6].

Self-organizing maps (SOM) [8], with its variants, have been extensively used to solve difficult high-dimensional and nonlinear problems such as feature extraction and classification of imagen. A SOM can be view as a neural network with unsupervised learning which maps the input space into processing units (neuros) while preserving the topology of the input data. In a similar way, the elastic network [2] was proposed by Durbin and Willshaw as an analogue approach to solve the Traveller Salesman Problem (TSP) by mapping an input point distribuion of cities into a geometrical output space.

In this article, we compare the use of a SOM and an elastic network to approach the problem of detecting the boundaries of skin pressure ulcers in preprocessed digital images. A new hybrid method is proposed here —self-organizing elastic map (SOEM)— that introduces an "elastic behaviour" in a SOM network, so that two different forces act over the neurons during the learning process: one approaching them to the input patterns —in a competitive way— and another moving them toward their neighboring neurons. In our experiments with artificial images and real clinical pressure ulcer images, classical elastic net [2] gave the lowest measurement errors and also the highest noise robustness, but at expense of getting a low computational efficiency.

2 SOM and elastic networks

2.1 Self-organizing maps

SOMs are inspired in the pioneering work of von der Malsburg [9] to propose a model of the visual cortex that is not completely determined by genetics but it is a self-organizing process where learnign plays an important role. Starting from this principles, Teuvo Kohonen [7] presented a simple model of self-organizing feature maps. The main propose of SOMs is to discover significant patterns or characteristics from input data in a unsupervised manner.

The most frequent two-dimensional topological structure of a SOM consists of $M = M_1 \times M_2$ processing units (neurons) placed on a rectangular grid so that vector $\overline{p}_i = (p_{i1}, p_{i2})$ gives the position of unit i. To establish a proximity notion between two neurons, a distance function is defined as $d(\overline{p}_i, \overline{p}_j) = \|\overline{p}_i - \overline{p}_j\|$ and usually implemented as Euclidean of rectangular distance. A neighborhood function of that distance between processing units is then defined and it will be used in the learning process to set the degree of weight change for each iteration of the algorithm. A typical neighborhood function is a negative exponential of distance: $\Lambda(\overline{p}_i, \overline{p}_j) = e^{-\|\overline{p}_i - \overline{p}_j\|}$.

$$\overline{w}_i(k+1) = \overline{w}_i(k) + \eta(k)\Lambda(\overline{p}_r, \overline{p}_i)(\overline{x}[k] - \overline{w}_i[k]),\ i = 1, 2, \ldots, M_1 \times M_2 \quad (1)$$

Equation 1 shows the learning rule of the traditional SOM algorithm, where $\overline{w}_i$ is the connection weight vector from the input pattern $\overline{x}$ —N-dimensional— to the neuron i and η is the learning rate which usually decreases linearly as a function of number of iterations of the algorithm. In this equation, r is the *winner* neuron, i.e. the processing unit with the largest synaptic potential ($h_r > h_i$, see eq. 2) at iteration k.

$$h_i = \sum_{j=1}^{N} w_{ij} x_j - \sum_{j=1}^{N} w_{ij}^2 / 2 \quad (2)$$

2.2 The elastic network

The elastic net algorithm was initially proposed by Durbin and Willshaw [2] as an alternative geometrical approach to solve the TSP for N cities. From this point of view, a tour was considered as a mapping from a circle to the plane so that each city in the plane is mapped to by some point in the circle. These mappings set from a circular path of points to the plane in which neighbouring points on the circle are mapped as close as possible on the plane. This is a special case of the general problem of best preserving neighbourhood relationships when mapping between different geometrical spaces. The elastic net algorithm is a procedure for the succesive recalculation of the position of M points in the plane in which cities lie. This points describe a closed path which is initially a small circle centered on the centre of the distribution of cities and is gradually elongated non-uniformly to pass eventually near all the cities. Each point on the path moves under the influence of two types of force: the first moves it towards those cities to which it is nearest (so depending on distance to the cities); the second pulls it towards its neightbours on the path, acting to minimize the total path length.

Equation 3 governs the way in what the position of a point j changes in each iteration of the algorithm. In this equation, $\overline{y}_i$ is the position of point j, $\overline{x}_i$ is the position of a city i, and α and β are two constants that determine the relative strengths of the forces from the cities and the neighbours of point j. The gradual increase of specificity of each city to its nearest points is regulated by the constant K. Finally, the coefficient w_{ij} specifies the influence of city i on path point j (connection strength), and is a functon of the distance $|\overline{x}_i - \overline{y}_j|$ and of the parameter K (see equation 4, where $\phi(d, K)$ is a positive, bounded decreasing function of distance d that approaches zero for $d > K$).

$$\Delta\overline{y}_j = \alpha \sum_i w_{ij}(\overline{x}_i - \overline{y}_j) + \beta K(\overline{y}_{j+1} - 2\overline{y}_j + \overline{y}_{j-1}) \tag{3}$$

$$w_{ij} = \phi(|\overline{x}_i - \overline{y}_j|, K) / \sum_l \phi(|\overline{x}_i - \overline{y}_l|, K) \tag{4}$$

In [2], Durbin and Willshaw compared their elastic net method with more conventional algorithms for computing tours of 100 cities distributed at random in the unit squeare. They got a best tour which was within 1% of the best tour length they found in their study (see table 1 and figure 1 in [2]).

The elastic net algorithm has been successfully used by several authors in computational models to explain the development of maps in primary visual cortex of mammals [1, 4, 5].

2.3 A self-organizing elastic map

In the model of the elastic network above (eq. 4), each point $\overline{y}_j$ has to be updated at each iteration of the algorithm, as a function of the distance to all the input patterns and its neighboring points. Equation 5 shows the dynamics of a now competitive elastic net, which we called SOEM, where the change of position of a point $\overline{y}_j$ in the output space is governed by two forces: 1) one that depends on the distance to the input pattern $\overline{x}_k$ presented at iteration k , and 2) another one that integrates the tension from neighbouring points $\overline{y}_i$. As in SOM, the competitive nature of the network is determined by a function $\Lambda(\overline{p}_r, \overline{p}_j)$ of the distance to the winning neuron r, where $\overline{p}_i = \overline{y}_{i,0}$.

$$\Delta\overline{y}_j = \eta(k)\Lambda(\overline{p}_r, \overline{p}_j)(\alpha w_{kj}[\overline{x}_k - \overline{y}_j] + \beta K[\overline{y}_{j+1} - 2\overline{y}_j + \overline{y}_{j-1}]) \qquad (5)$$

3 results

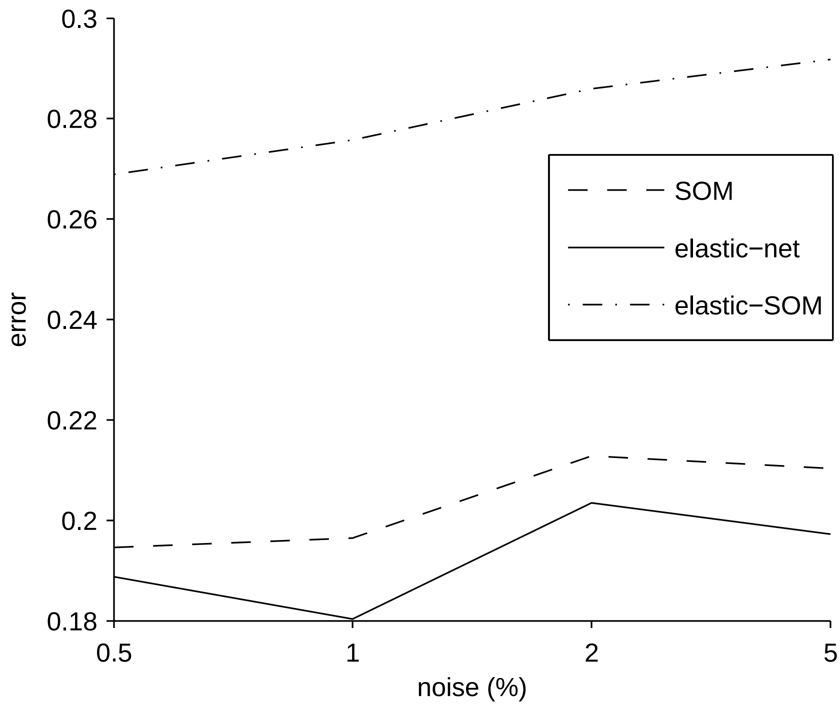

Fig. 1. Error for different netwoks

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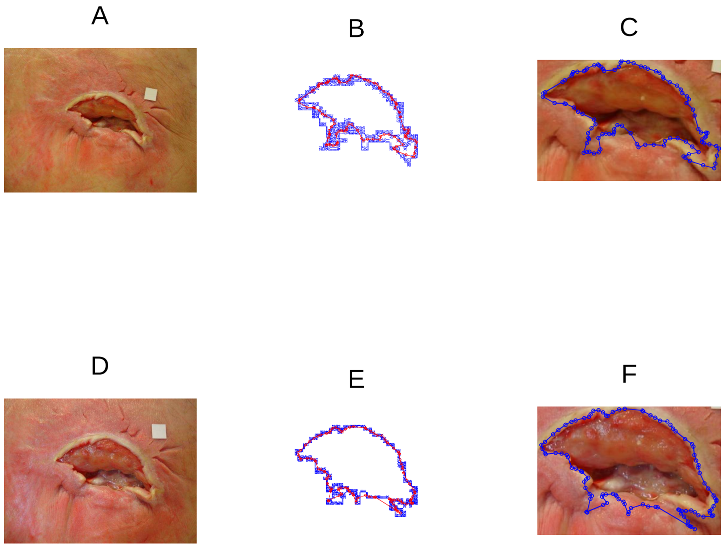

Fig. 2. Best results with elastic net

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