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Self-organizing neural networks based on spatial isomorphism for active contour modeling☆

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Abstract

The problem considered in this paper is how to localize and extract object boundaries (salient contours) in an image. To this end, we present a new active contour model, which is a neural network, based on self- organization. The novelty of the model consists in exploiting the principles of *spatial isomorphism* and *self-organization* in order to create flexible contours that characterize shapes in images. The flexibility of the model is effectuated by a locally co-operative and globally competitive self-organizing scheme, which enables the model to *cling* to the nearest salient contour in the test image. To start with this deformation process, the model requires a rough boundary as the initial contour. As reported here, the implemented model is semi-automatic, in the sense that a user-interface is needed for initializing the process. The model's utility and versatility are illustrated by applying it to the problems of boundary extraction, stereo vision, bio-medical image analysis and digital image libraries. Interestingly, the theoretical basis for the proposed model can be traced to the extensive literature on Gestalt perception in which the principle of psycho-physical isomorphism plays a role. © 2000 Pattern Recognition Society. Published by Elsevier Science Ltd. All rights reserved.

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1. Introduction

A goal of computational vision is to extract the shapes of two- and three-dimensional objects from images of physical scenes. To this end, most of the present literature deals with model-based techniques which use a model of the object whose boundary representation is matched to the image in order to extract the boundaries of the object. The models used in such a process could be either rigid, as in the case of simple template-matching approaches, or non-rigid, as in the case of deformable models. The latter, which *deform* themselves in the process of matching, have come to be known as active contour models (ACM). It is to be noted that the word *active* is used to represent the dynamical nature of the models in the process of matching. Because these active contour models are more flexible than the earlier rigid models, they have been effectively employed in resolving various problems in vision: stereo matching [2], motion tracking [2,3], detection of subjective contours [2], segmenting biomedical images, [3,4] face recognition [5,6], and so on.

In this paper, we propose a new active contour model based on self-organization. This model *completely* differs from the other models in both the underlying theory and implementation. We utilize a modification of the neural-network model proposed by Ganesh Murthy and Venkatesh [7] and utilized by Shanmukh et al. [8], who, for pattern classification, employ self-organizing networks

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(SON), which are spatially isomorphic to patterns. While exploiting the simplicity and elegance of the above model, we modify the underlying theory to fit the problem of contour extraction. An analogy, which closely relates the model to the age-old theory of psycho-physiological isomorphism [9], is presented as a possible theoretical basis for its development.

The paper is organized as follows: Section 2 describes the existing ACM and the various approaches used towards achieving the goal of modeling contours. Section 3 presents an analogy relating the model to the concept of psycho-physiological isomorphism. Section 4 is concerned with the application of the concept of spatial isomorphism (with respect to neural networks) to character and object recognition [7,8,10]. Section 5 presents the proposed active contour model, along with a description of the constraints imposed and the various methods of initialization. Section 6 discusses the implementation details of the approach, listing its distinct characteristics and advantages. Section 7 describes the applications of the model to contour extraction, stereo-image analysis, biomedical image interpretation, and image libraries. Section 8 concludes the paper.

2. Existing ACM's

The *snake* [2] is probably the first proposed ACM, which is a controlled continuity-spline under the influence of internal (spline), image and external (constraint) forces. The internal spline forces impose a smoothness constraint, while the image forces push the snake towards salient features (lines, edges, subjective contours, etc.). The external constraint forces, on the other hand, are responsible for placing the snake near the desired local minimum, and originate from the choice of the initial contour, which, in turn, is governed by higher level image interpretation algorithms.

The problem of contour modeling is then cast in the framework of energy minimization, with the energy functions consisting of terms corresponding to the internal, image and external forces. The internal spline energy involves first and second order terms, controlled by parameters which are themselves functions of the parameter representing the position of the snake. The image force, on the other hand, involves weighted values of line, edge and termination functionals. Finally, the external constraint force is used to select a local minimum of the chosen energy function.

In the attempt to overcome some of the shortcomings of the *snake* model, the ACM's proposed in the literature either modify the energy functionals used in the original *snake* model or propose new approaches, a few of which are discussed below.

Leymarie and Levine [3] employ the *snake* model for segmenting a noisy intensity image, and for tracking a non-rigid object in a plane. They also propose an improved terminating criterion (for the optimization scheme in the snake model) on the basis of topological features of the graph of the intensity image.

Amini et al. [11] discuss the problems associated with the original *snake* model, and present an algorithm for active contours based on dynamic programming. They formulate the optimization problem as a discrete multistage decision process, and solve it using a time-delayed discrete dynamic programming algorithm.

Cohen [12] proposes a "balloon" model as a way to generalize and solve some of the problems encountered with the original *snake* model. Cohen introduces an internal pressure force by regarding the curve or surface as a balloon which is inflated, and modifies the internal and external forces used in the *snake* model by adding the pressure force, so that the boundary is pushed out as if air is introduced inside. Cohen [4] generalizes the balloon model to a 3-D deformable surface (which is generated in 3-D images).

Lai and Chin [13] propose a global contour model, called the generalized active contour model, or *g-snakes*. Their active contour model is based on a shape matrix which, when combined with a Markov random field (used to model local deformations), yields a prior distribution that exerts influence over the global model, while allowing for deformations. Moreover, they claim that their internal energy function, unlike the *snake* model (which constrains the solution to the class of controlled continuity splines), is more general because it allows incorporation of prior models to create bias towards a particular type of contour. Lai and Chin [14], present a min–max criterion which automatically determines the optimal regularization at every location along the boundary.

Chiou and Hwang [15] suggest a neural-network-based stochastic active contour model in which a feed-forward neural network is used to build a knowledge base of distinct features so that the external energy function used in the *snake* model can be formulated systematically.

Staib and Duncan [16] consider parametrically deformable models for boundary finding which is formulated as an optimization problem for estimating the maximum of the *a posteriori probability* function (MAP). They apply flexible constraints, in the form of a probabilistic deformable model, to the problem of segmenting natural 2-D objects whose diversity and irregularity of shape preclude their representation in terms of fixed features or form.

Malladi et al. [17] describe a new ACM based on a level-set approach for recovering the shapes of objects in two and three dimensions. According to them, the parametric boundary representation schemes (similar to the *snake* model) will encounter difficulties when the dynamic model embedded in a noisy data set expands/

shrinks along a normal field. They further report that their modeling technique avoids the Lagrangian geometric view (as in *snakes*), but instead capitalizes on a related initial-value partial differential equation.

Jain et al. [18] employ deformable templates (which are also, in a sense, ACM's) for object matching. Here, prior knowledge of an object shape is described by (i) a prototype template characterized by representative contours/edges; and (ii) a set of probabilistic deformation transformations on the template. A Bayesian scheme, which is based on this prior knowledge and the edge information in the input image, is used to find a match between the deformed template and the objects in the image.

3. Gestalt psychology and isomorphism

Psycho-physiological (or psycho-physical) isomorphism is the theory that patterns of perception and of cerebral excitation show a one-to-one topological correspondence in which the spatial and temporal orders of items and events in the conscious and cerebral fields are the same, although spatial and temporal intervals between items and events (while they may correspond in their orders) do not agree in their magnitudes [9]. This view has a considerable history and plays an important role in the Gestalt school of psychology (cf. Chapter VIII in Hernstein and Boring [9]).

A set of points is said to be isomorphic to another set of points, if every point in one corresponds to a point in the other, and the topological relations or spatial orders of the points are the same in the two.[2] The Gestalt psychologists believed that the distribution of electrical activity within the brain resembles the shape of the object seen. This apparent resemblance between perception and brain activity plays a prominent role in Gestalt theory [20].

The proposed approach can be brought into this framework of psycho-physiological isomorphism because it creates a network of neurons topologically equivalent to (*or isomorphic to*) the points in the image plane (see Section 5), or a one-to-one correspondence is made between the image points and the neurons.

The theory of isomorphism, apparently reasonable in principle, turns out to be wrong, as evident from the recent findings about the functioning mechanisms of the mammalian brains, which clearly show that the visual world is not represented as an isomorphic picture within the brain [20]. Retinal signals (from the 130 million and odd receptors) pass through the (one million or so of) retinal ganglion cells which collate messages from the numerous photoreceptors, and summarize them in a biologically relevant manner. Observe that there cannot exist, theoretically, a one-to-one mapping from the retinal receptors to the retinal ganglion cells in view of the 130 : 1 compression factor. (It should be noted that this observation is made in a general context because there may be one-to-one correspondence between retinal receptors and ganglion cells in case of the receptors in the foveal region of retina [21].) The neural signals from the ganglion cells, then, pass through the superior colliculus and the lateral geniculate nucleus on the way to the visual cortex. The current interpretation is that the theory of isomorphism cannot be valid since there is no one-to-one mapping from the retinal receptors to the visual cortex.

4. Character and object recognition

In this section, we discuss the application of spatial isomorphism to character and object recognition [7,8,10]. The human vision system recognizes patterns in spite of scale changes, rotation and shift. Possibly, this is achieved by a conscious establishment of correspondence between significant features of the model and those of the retinal image. The result of classification then depends on the ease of correspondence of the given pattern with each of the model images (exemplars). The exemplar with which the correspondence is established most easily could then be considered as the class to which the test pattern belongs. In other words, human recognition is perhaps guided by the amount of mental deformation the exemplar has to undergo to match the given unknown pattern.

This idea of using a deformation strategy and a corresponding deformation measure for classification has been successfully exploited (with very good accuracy) by Ganesh Murthy and Venkatesh [7] and by Shanmukh et al. [8], for the recognition of 2-D objects and characters, subject to rotation and scaling. Here, a binary template of each and every model is stored as a model image (exemplar). During the recognition phase, a network of neurons is created for each of the exemplars, with the neurons in each network arranged in exactly the same way as the pixels of the corresponding exemplars are. That is, the network created is spatially isomorphic to the exemplars. Then, a locally co-operative weight-updating scheme is used to deform each of the networks so as to establish the correspondence between the test pattern and the exemplars.

Once the mappings of the networks onto the test pattern are established, a deformation measure is used to find the network which has undergone the least

[2] If a system of points is marked on a flat rubber membrane, and the membrane is then stretched tightly over some irregular surface, then the points in the stretched membrane are isomorphic to the points in the flat membrane [19].

deformation to establish this mapping, and the test pattern is classified to be the pattern corresponding to the network. The method uses a self-organization scheme similar to Kohonen's [22] algorithm, but is completely different from it *in terms of architecture*. Explicitly, the method *does not* employ the neural architecture with a lattice of neurons, typical of Kohonen's network.

5. Proposed active contour model

In the course of exploiting the simplicity and efficiency of the above approach [7,8], we modify it so as to be applicable to the problem of contour extraction. The present model, in common with most of the present ACM's, requires an initial contour (see Section 5.2 below), starting from which it evolves. A neural network isomorphic to this initial contour is constructed, and subjected to deformation in order to map onto the nearest salient contour in the image. The correspondence between the salient contour and the network is established by mapping the latter onto the former by using the self-organization scheme [22,10]. The steps involved in such a mapping are as follows:

1. Compute the edge map of the test image.
2. Set the initial contour from where the system has to start, using a suitable initialization scheme (see Section 5.2 below). Choose the region of interest according to the location of the initial contour. (The region of interest is a rectangle enclosing all the points of the initial contour.)
3. Obtain the edge points $E = \{(x_i, y_i), i = 1, \ldots, N_e\}$ within the region of interest, where N_e is the number of edge points within the region of interest.
4. Construct a network with N_c neurons, where N_c is the number of points on the initial contour. Each neuron in the network receives two inputs (I_1, I_2). The weights $w^i = (w_1^i, w_2^i)$, $i = 1, \ldots, N_c$, corresponding to these two inputs, are initialized to the co-ordinates of points on the initial contour. In effect, construct a neural network isomorphic to the initial contour.
5. Repeat the following steps a certain number of times (N_{iter}):

   (i) Select a point $\mathrm{p} = (u,v) \in E$ randomly, and feed the (x,y) coordinates of the selected point p as inputs (I_1, I_2) to every neuron in the network.

   (ii) Determine the neuron whose weight vector is closest (w.r.t. Euclidean distance measure) to the input vector, and declare it as the winner neuron. If the distance between the winner neuron's weight vector (w^w) and the input vector is greater than a particular threshold T_{wd}, then go to (i).

   (iii) Update the weights of the neurons in the network using the following rule:

   For neuron i,

   $$w^i = w^i + \eta * \mathrm{e}^{-\|\mathrm{w}^w - \mathrm{w}^i\|^2/2*\sigma^2} * (\mathrm{p} - w^i), \tag{1}$$

   where η, σ are the standard learning rate and neighborhood parameters.

   (iv) Calculate the parameter C_{np} (neighborhood parameter) of the contour as:

   $$C_{np} = \mathrm{Max}\{\mathrm{Max}(|w_1^i - w_1^{i+1}|, |w_2^i - w_2^{i+1}|): 1 \leqslant i \leqslant N_c - 1\}. \tag{2}$$

   If $C_{np} > T_{np}$, the threshold value of the neighborhood constraint parameter, then restore the previous network weights discarding the present update.

   (v) Vary η and σ according to the following rules:

   $$\sigma = \sigma_{init} * (\sigma_{fin}/\sigma_{init})^{iter/N_{iter}},$$

   $$\eta = \eta_{init} * (\eta_{fin}/\eta_{init})^{iter/N_{iter}},$$

   where σ_{init} and σ_{fin} are the initial and final values of σ; η_{init} and η_{fin} are those of η; and *iter* is the current iteration number.

5.1. Constraints employed in the model

The proposed ACM entails bounds on (i) the winner-distance (WD); and (ii) the neighborhood parameter (NP), which implicitly impose the smoothness constraint. In order to contrast this with the results of the literature, recall that, in the *snake* model, the image, internal and external constraint forces are made explicit, and an energy function associated with these forces is minimized to obtain the final contour. The internal forces in the proposed model are implicitly imposed by the constraints mentioned above, and the image forces are taken care of by the input fed to the network. As far as the external constraint force is concerned, it is made implicit by virtue of the fact that the initial contour is provided by higher level interpretation processes (see Section 5.2). Finding appropriate bounds for WD and NP is a critical step. We now describe the purpose of these constraints (bounds) and their effect on the model's performance.

5.1.1. Constraint on the winner-distance (WD)

This constraint on the winner-distance (WD) is useful in avoiding the influence of edge points which are within the region of interest, but are not a part of the nearest salient contour of interest (spurious edge points). In the absence of such a constraint, the neurons "organize" themselves to spurious edges, thereby affecting the proper extraction of the desired contour.

The constraint places a threshold, T_{wd}, on the WD, controlling the updating or otherwise of the weights of

Fig. 1. Illustration of the WD constraint (clock-wise from top-left): (a) initial contour overlayed on the image; (b) edge map of the image showing spurious internal edges; (c) final contour overlayed on the image.

the network: if the distance between the input vector and the winner neuron's weight vector is greater than T_{wd}, then the weights of the network are not updated. This constraint has, in fact, been made explicit in Step 5(ii) of the above algorithm. The lower the value of T_{wd}, the greater is the constraint on the updating. In other words, if this parameter is assigned a larger value, the neurons in the network tend to organize themselves with respect to spurious *inner* points which are at larger distances from the salient contour of interest. On the other hand, if it is *too* low, the weights will never be updated in spite of the input point lying on the salient contour. The utility of this constraint is shown in Fig. 1, where the active contour model organizes itself to the ellipse in spite of the spurious edge points within the ellipse.

5.1.2. *Constraint on neighborhood*

The neighborhood parameter (NP) refers to the maximum of the distances in the x- and y-directions, taken over all the adjacent pairs of points on the contour. Constraining this parameter helps in maintaining the continuity of the contour in the course of its deformation. In the absence of a constraint on this parameter, many neurons tend to organize themselves towards a *single* point of the input image, leading to discontinuities in the final contour. The threshold parameter on the NP, T_{NP}, which is essentially the maximum permitted distance between neighboring neurons, is used in Step 5(iv) of the above algorithm (see Eq. (2)). The usefulness of this constraint is illustrated in Fig. 2, where a higher value of T_{np} leads to a highly broken contour, while a lower value gives a continuous contour.

5.2. *Initialization*

As mentioned earlier, the proposed method requires a rough boundary as the initial contour to start with the deformation process. This initialization can be achieved in a number of ways, depending on the application. We discuss some of them here.

For static scenes, the generalized Hough transform technique [13,23] can be employed to initialize the contour, thereby exploiting the efficiency and globality of Hough transform in the presence of noise and boundary gaps. On the other hand, in an active vision system with movable (and multiple) cameras, two or more images could be acquired, and subjected to optical flow analysis or image differencing techniques, the results of which could be used to initialize the contour. For illustration purposes, in the results presented in the following

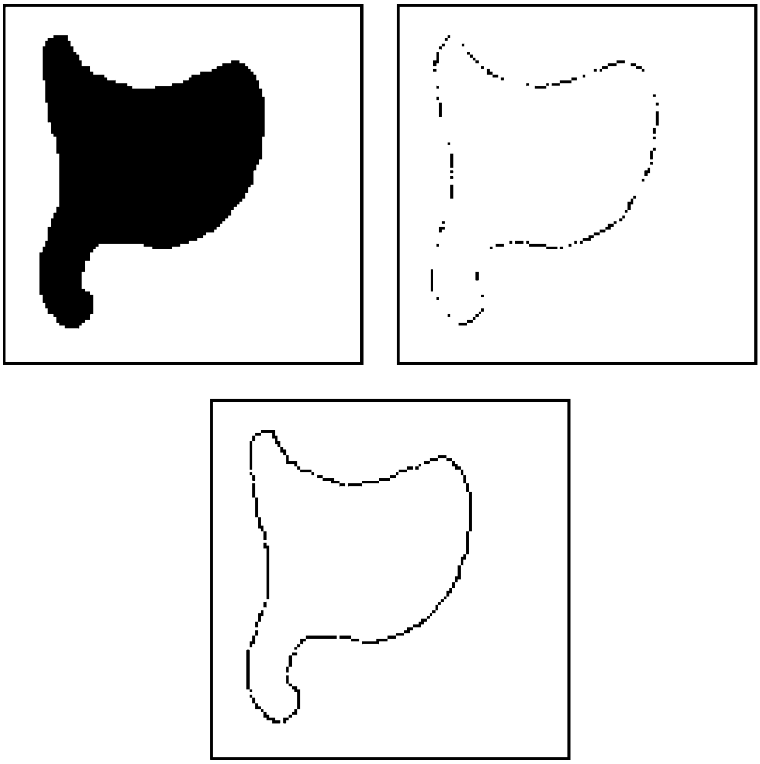

Fig. 2. Illustration of the NP's utility (clock-wise from top-left): (a) input image; (b) high value of $T_{np}(= 10.5)$ leads to broken contour; (c) low value of $T_{np}(= 2.0)$ leads to a continuous contour.

sections, an user-interface is employed for the initialization (of the contour), which has been used in the literature [2,13] for the same purpose.

6. Implementation and results

The proposed method was implemented in C++ with X11 for graphical user-interface. The experiments were conducted on a HP9000/715 workstation. For an image of size 128×128, the program takes 5–6 s to arrive at the final contour. Typical values of important parameters used in the above system are as follows:

- Number of iterations, $N_{iter} = 300$–600, depending upon the size and shape of the contour.
- Initial value of σ, $\sigma_{init} = 3$–5.
- Final value of σ, $\sigma_{fin} = 0.1$–0.3.
- Initial value of the learning rate parameter, η, $\eta_{init} = 0.7$–0.9.
- Final value of η, $\eta_{fin} = 0.001$–0.01.
- Threshold parameters, T_{np}, T_{wd}, lie in the range 2–5.

The selection of the above parameters depends on the application as also on the images. A discussion on the necessity and the effect of the parameters T_{np} and T_{wd} on the model's performance was presented earlier in Section 5.1. Further, the size of the network depends on the nature of the initial contour. This is evident from the way the network is constructed (Section 5). Evidently, if the initial contour consists of n pixel-points, the size of the network is n.

The parameter σ, which defines the neighborhood relation, describes the local co-operativeness of weight update in the network. If this parameter is large, the *influence* of the winner neuron extends to a larger neighborhood, leading to undesirable effects (like many neurons organizing towards a single image point). If this parameter is too low, then only the winner neurons will effectively be updated, depriving the algorithm of the advantages of local co-operativeness and self-organization. The selection of σ_{init} and σ_{fin} should be such that, initially, a larger neighborhood is influenced by the winner, and, finally, the influence restricted to the winner neuron alone.

The parameter η, on the other hand, defines the amount of update forced on the weights of the neurons. It is reduced from a higher value to a lower value, with the idea of allowing a greater movement of weights towards edge points in the initial stages (when the weights are far from them), and a smaller movement of weights towards the end (when the weights are nearer to the edge points).

Now, on the basis of the experimental findings, we summarize some distinct characteristics of the proposed method:

- The method is immune to noise present in the input image. The network can extract the nearest salient contour from a noisy image, as illustrated in Fig. 3 where the contour has been extracted successfully, even though the percentage of noise is 20.
- The method can be used to extract salient, open contours from a given noisy image, as shown in Fig. 4.
- The method can extract contours even in the presence of kinks in the initial contour. Fig. 5a shows the initial contour being pulled off from the actual salient contour. The final contour is shown in Fig. 5b, where the network has deformed and 'snapped' itself appropriately to the actual contour.

6.1. Advantages

On the basis of the examples given above, we summarize the advantages of the proposed ACM approach:

1. It is robust with respect to noise in the given image.
2. There is no need to choose energy functions, since the problem is not cast in an optimization framework.
3. Every point in the contour is extracted, which is of considerable importance in stereo matching and motion tracking.
4. As applied to the disparity estimates in stereo image analysis, the approach is believed to be novel. The solution to the correspondence problem is simpler.
5. It is possible to generalize the approach to (i) allow information other than mere coordinates of edge points (e.g. directional information); and (ii) the classification of contours.

7. Applications of the model

The proposed model, as mentioned earlier, is applicable to localizing and extracting boundaries in the course of segmenting image data (Figs. 1 and 4). In what follows, we present some of the other applications of the model: stereo-vision, bio-medical image analysis and digital image libraries.

7.1. Stereo-vision

The proposed ACM provides a novel technique to efficiently extract and match, point-by-point (for

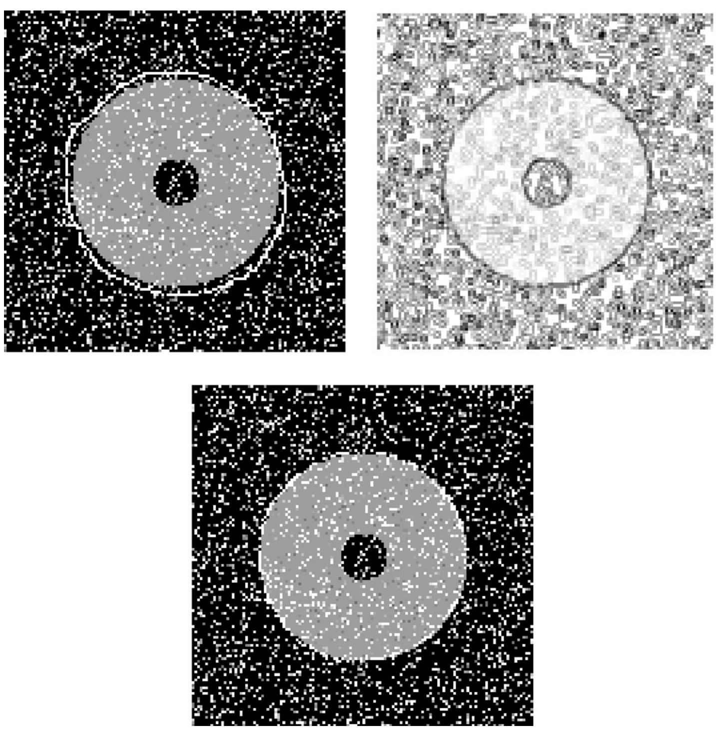

Fig. 3. Illustration of the robustness of the approach to noise (clock-wise from top-left): (a) initial contour overlayed on the image; (b) edge map of the image; (c) final contour overlayed on the image.

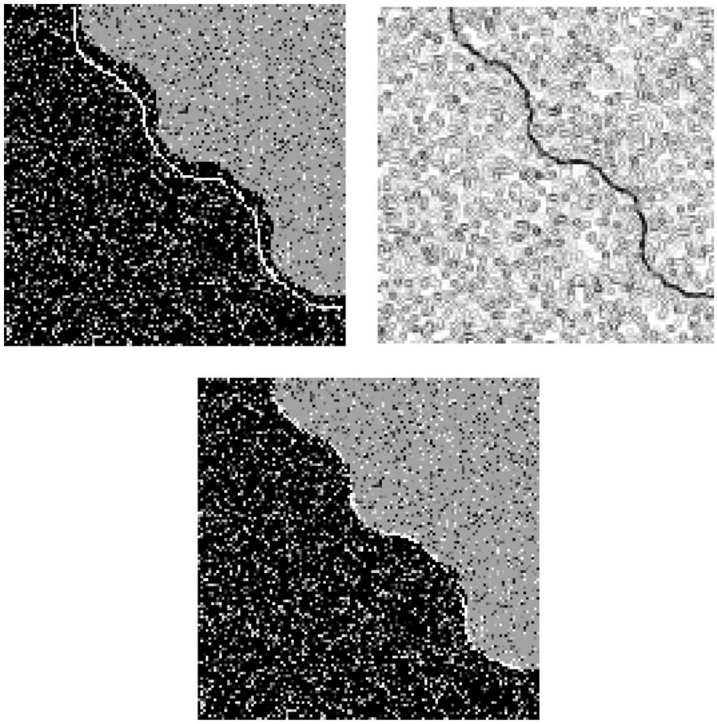

Fig. 4. Illustration of the capability of the approach in extraction of open contours (clock-wise from top-left): (a) initial contour overlayed on the image; (b) edge map of the image; (c) final contour overlayed on the image.

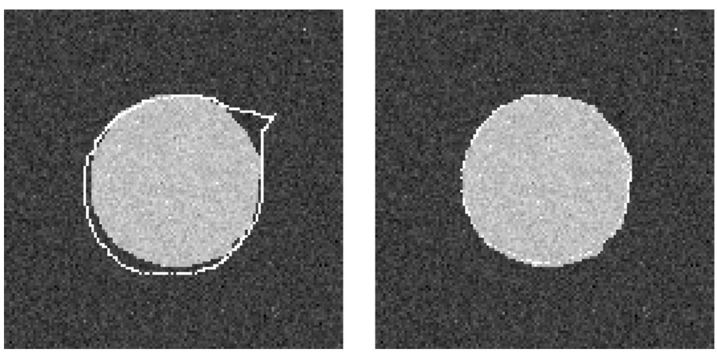

Fig. 5. (a) Initial contour overlaid on the image showing a part of it away from the salient contour. (b) Final contour illustrating the ability of the model in "snapping" itself to the nearest salient contour.

disparity estimates), the corresponding contours from the left and right images of a stereo-pair of images. We outline below the steps involved in solving this correspondence problem. Fig. 6a shows a stereo-pair of images which are to be matched for depth extraction.

1. Extract contours from both the left and right images of the stereo pair. (We call them left and right contours, respectively.)
2. Form a neural network isomorphic to either the left or the right contour. That is, form a network, with weights of the neurons set to the co-ordinates of the contour points. Without loss of generality, we assume that the network is constructed isomorphic to the left contour.
3. Present each point from the right contour to each neuron in the network, and use the updating scheme described for contour extraction in Section 5. Dispense with the WD and NP constraints.
4. When the network converges, it is *isomorphic* to the right contour. The initial and final weights of a particular neuron will be the corresponding contour

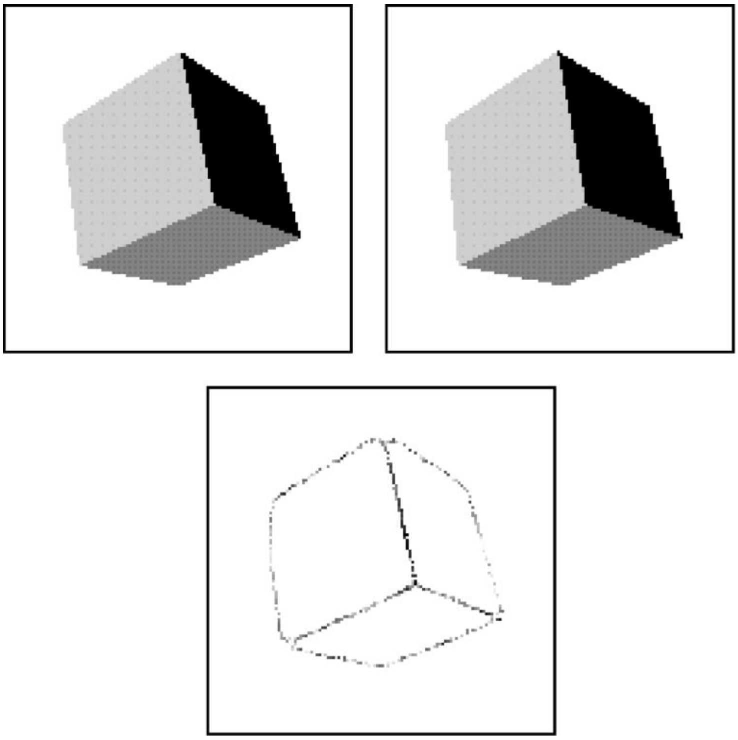

Fig. 6. Illustration of the ability of the approach in analyzing stereo images: (a) (top) stereo pair; (b) disparity map.

points in the left and right images respectively. Also, assuming epipolar geometry, the difference between the X co-ordinates of the initial and final weights of any particular neuron gives the disparity at that point (which can be used to calculate the depth of the point).

The disparity map is shown in Fig. 6b in which intensity is directly proportional to the disparity (and inversely proportional to the depth). In the example shown, the disparity map for the cube was obtained by (i) initializing contours for the three surfaces (see Fig. 6a) separately; (ii) calculating the disparity for each of them separately; and (iii) finally merging them together.

7.2. Bio-medical image interpretation

Imaging techniques like magnetic resonance imaging (MRI), X-ray computed tomography (CT) and positron emmision tomography (PET) provide detailed information regarding the anatomical and physiological function of various parts of the body. The interpretation of the data has been hindered by the inability to relate such information with specific anatomical regions. This is a consequence of the interpretation difficulties that arise due to small variations in anatomy [24]. Because the earlier models for shape are rigid, it is not possible to accommodate these variations for better interpretation. This can be achieved by employing active contour models, which deform themselves in the process of extracting the boundaries. Furthermore, medical applications, like cardiac boundary tracking, tumor volume quantification, cell tracking, etc., require extracting exact shapes in two and three dimensions. These also have been challenging tasks because of the amount of noise inherent in medical images.

We have already demonstrated that the proposed approach is noise-tolerant (Section 6). Now, we illustrate the extraction of implicit boundaries from bio-medical images in order to facilitate easy interpretation of anatomical parts. Fig. 7a shows an ultra-sound image of the head, overlaid with the initial contour. Fig. 7b illustrates the ability of the approach in extracting the contour information implicitly present in the image.

7.3. Object retrieval and image libraries

The proposed active contour model can be considered as a deformable template for application to the problem of locating and retrieving an object from a complex image. A solution to this problem is of significance to applications, like image database retrieval, object recognition and image segmentation. The proposed approach can be employed in a fashion similar to the one reported by Jain et al. [18]. In this context, it is assumed that

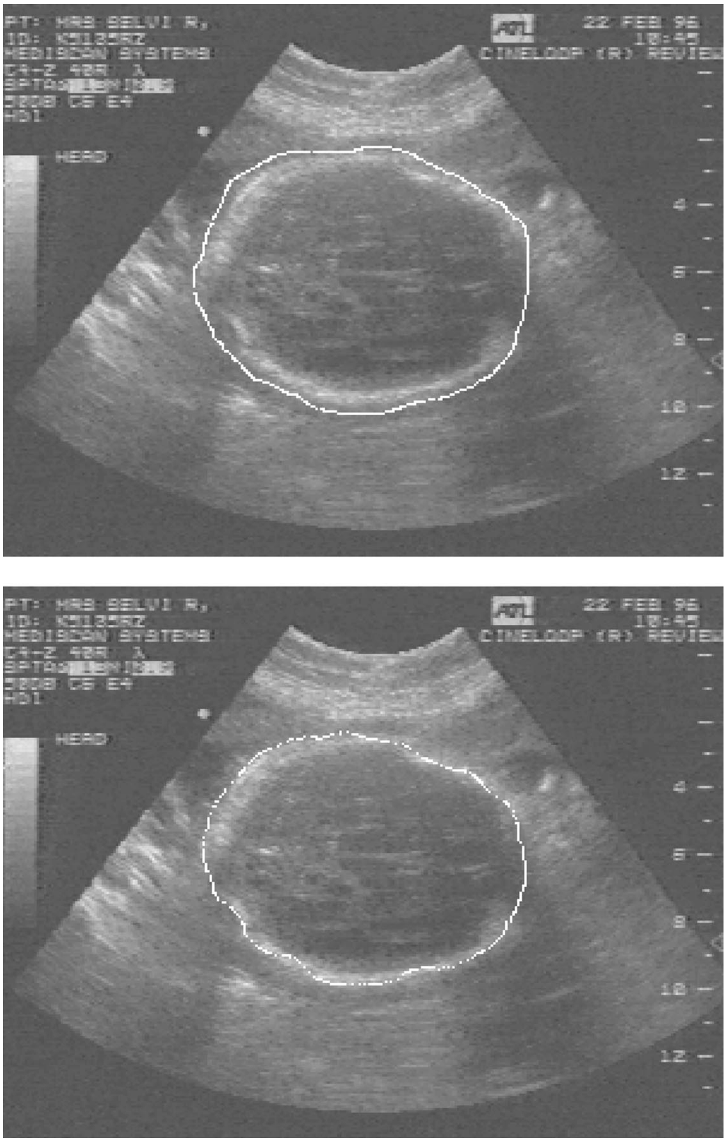

Fig. 7. Illustration of the ability of the approach in analyzing bio-medical images: (a) (top) initial contour overlaid on the image; (b) final contour overlaid on the image.

a priori information is available in the form of an inexact model of the object, which needs to be matched with the object in the input image.

Since the proposed contour model yields a continuous set of points as output after the deformation and matching, it is possible to use the model as a deformable template in object matching applications. The weights of the model are initialized with the co-ordinates of the binary template, and deformation is realized in much the same way as described in the algorithm of Section 5. The only difference lies in the search of the parameter space corresponding to scale, shift and rotation of the pattern, with the model initialized by the transformed versions of the binary template. However, the disadvantage of using such an approach (as with the one found in Jain et al. [18]) is the amount of time required in searching the entire parameter space. This can be reduced by the use of a coarse-to-fine matching strategy [18]. Further, the dimension of the parameter space of Jain et al. [18] is high because the deformations are also considered as parametric functions. If the proposed approach is applied to such a problem, the dimension of the parameter space reduces to four, corresponding to rotation, scale and shifts in X- and Y-directions. This is a consequence of the fact that the deformation is handled by the active contour model itself.

8. Conclusions

In order to localize salient contours in an image, a new active contour model (ACM), which is a neural network based on self-organization, is presented. It turns out that the theoretical basis for the proposed model can be traced to the extensive literature on Gestalt perception in which the principle of psycho-physical isomorphism plays an important role.

The main contribution of the proposed model is the exploitation of the principles of *spatial isomorphism* and *self-organization* in order to create flexible contours characterizing shapes in images. The deformation in the contour model is effectuated by a locally co-operative and globally competitive self-organizing scheme, which enables the model to *cling* to the nearest salient contour in the test image. To start with this deformation process, the model requires a rough boundary as the initial contour. Various methods for this initialization are discussed. As reported here, the model is a semi-automatic method, in the sense that an user-interface is needed for this initialization purpose.

The effect of the important parameters on the model's performance and the difficulty in choosing them are elaborated. The utility and versatility of the model are illustrated by applying to the problems of boundary extraction, stereo vision, bio-medical image analysis and digital image libraries.

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