Emergent Segmentation of Topological Active Nets by Means of Evolutionary Obtained Artificial Neural Networks

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Abstract: We developed a novel segmentation method using deformable models. As deformable model we used Topological Active Nets, model which integrates features of region-based and boundary-based segmentation techniques. The deformation through time is defined by an Artificial Neural Network (ANN) that learns to move each node of the segmentation model based on its energy surrounding. The ANN is applied to each of the nodes and in different temporal steps until the final segmentation is obtained. The ANN training is obtained by simulated evolution, using differential evolution to automatically obtain the ANN that provides the emergent segmentation. The new proposal was tested in different artificial and real images, showing the capabilities of the methodology.

1 INTRODUCTION AND PREVIOUS WORK

The active nets model for image segmentation was proposed (Tsumiyama and Yamamoto, 1989) as a variant of the deformable models (Kass et al., 1988) that integrates features of region–based and boundary–based segmentation techniques. To this end, active nets distinguish two kinds of nodes: internal nodes, related to the region–based information, and external nodes, related to the boundary–based information. The former model the inner topology of the objects whereas the latter fit the edges of the objects. The Topological Active Net (TAN) (Ansia et al., 1999) model was developed as an extension of the original active net model. It solves some intrinsic problems to the deformable models such as the initialization problem. It also has a dynamic behavior that allows topological local changes in order to perform accurate adjustments and find all the objects of interest in the scene. The model deformation is controlled by energy functions in such a way that the mesh energy has a minimum when the model is over the objects of the scene. This way, the segmentation process turns into a minimization task.

The energy minimization of a given deformable model has been faced with different minimization techniques. One of the simplest methods is the greedy strategy (Williams and Shah, 1992). The main idea implies the local modification of the model in a way the energy of the model is progressively reduced. The segmentation finishes when no further modification implies a reduction in terms of energy. As the main advantages, this method is fast and direct, providing the final segmentations with low computation requirements. However, as a local minimization method, it is also sensitive to possible noise or complications in the images. This method was used as a first approximation to the energy minimization of the Topological Active Nets (Ansia et al., 1999).

As the local greedy strategy presented relevant drawbacks, especially regarding the segmentation with complex and noisy images, different global search methods based on evolutionary computation were proposed. Thus, a global search method using genetic algorithms (Ibáñez et al., 2009) was designed. As a global search technique, this method provided better results working under different complications in the image, like noise or fuzzy and complex boundaries, situations quite common working under real conditions. However, this approach presented an important drawback, that is the complexity. The segmentation process needed large times and computation requirements to reach the desired results. As an improvement of the genetic algorithm approach, another evolutionary optimization technique was proposed (Novo et al., 2011). This new approach, based in differential evolution, allowed a simplification of the previous method and also speed up the segmentation process, obtaining the final results in less genera-

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tions (implying less time).

There is very little work regarding emerging systems and deformable models for image segmentation. "Deformable organisms" were used for an automatic segmentation in medical images (McInerney et al., 2002). Their artificial organisms possessed deformable bodies with distributed sensors, while their behaviors consisted of movements and alterations of predefined body shapes (defined in accordance with the image object to segment). The authors demonstrated the method with several prototype deformable organisms based on a multiscale axisymmetric body morphology, including a "corpus callosum worm" to segment and label the corpus callosum in 2D midsagittal MR brain images.

In this paper, we used Differential Evolution (DE) (Price and Storn, 1997)(Price et al., 2005) to train an Artificial Neural Network (ANN) that works as a "segmentation operator" that knows how to move each TAN node in order to reach the final segmentations. Section 2 details the main characteristics of the method. It includes the basis of the Topological Active Nets, deformable model used to achieve the segmentations (Sub-section 2.1), the details of the ANN designed (Sub-section 2.2) and the optimization of the ANN parameters using the DE method (Sub-section 2.3). In Section 3 different artificial and real images are used to show the results and capabilities of the approach. Finally, Section 4 expounds the conclusions of the work.

2 METHODS

2.1 Topological Active Nets

A Topological Active Net (TAN) is a discrete implementation of an elastic $n-$dimensional mesh with interrelated nodes (Ansia et al., 1999). The model has two kinds of nodes: internal and external. Each kind of node represents different features of the objects: the external nodes fit their edges whereas the internal nodes model their internal topology.

As other deformable models, its state is governed by an energy function, with the distinction between the internal and external energy. The internal energy controls the shape and the structure of the net whereas the external energy represents the external forces which govern the adjustment process. These energies are composed of several terms and in all the cases the aim is their minimization.

Internal Energy Terms. The internal energy depends on first and second order derivatives which control contraction and bending, respectively. The internal energy term is defined through the following equation for each node:

$$\begin{aligned} E_{int}(v(r,s)) = \;& \alpha\,(|v_r(r,s)|^2 + |v_s(r,s)|^2) + \\ & \beta\,(|v_{rr}(r,s)|^2 + |v_{rs}(r,s)|^2 + |v_{ss}(r,s)|^2) \end{aligned} \tag{1}$$

where the subscripts represent partial derivatives, and α and β are coefficients that control the first and second order smoothness of the net. The first and second derivatives are estimated using the finite differences technique.

External Energy Terms. The external energy represents the features of the scene that guide the adjustment process:

$$E_{ext}(v(r,s)) = \omega\, f[I(v(r,s))] + \frac{\rho}{|\aleph(r,s)|} \sum_{p \in \aleph(r,s)} \frac{1}{\|v(r,s) - v(p)\|} f[I(v(p))] \tag{2}$$

where ω and ρ are weights, $I(v(r,s))$ is the intensity of the original image in the position $v(r,s)$, $\aleph(r,s)$ is the neighborhood of the node (r,s) and f is a function, which is different for both types of nodes since the external nodes must fit the edges whereas the internal nodes model the inner features of the objects.

If the objects to detect are bright and the background is dark, the energy of an internal node will be minimum when it is on a point with a high grey level. Also, the energy of an external node will be minimum when it is on a discontinuity and on a dark point outside the object. Given these circumstances, the function f is defined as:

$$f[I(v(r,s))] = \begin{cases} IO_i(v(r,s)) \;+\; \tau IOD_i(v(r,s)) & \text{for internal nodes} \\ IO_e(v(r,s)) \;+\; \tau IOD_e(v(r,s)) \;+ & \text{for external} \\ \xi(G_{max} - G(v(r,s))) \;+\; \delta GD(v(r,s)) & \text{nodes} \end{cases} \tag{3}$$

where τ, ξ and δ are weighting terms, G_{max} and $G(v(r,s))$ are the maximum gradient and the gradient of the input image in node position $v(r,s)$, $I(v(r,s))$ is the intensity of the input image in node position $v(r,s)$, IO is a term called "In-Out" and IOD a term called "distance In-Out", and $GD(v(r,s))$ is a gradient distance term. The IO term minimizes the energy of individuals with the external nodes in background intensity values and the internal nodes in object intensity values meanwhile the terms IOD act as a gradient: for the internal nodes (IOD_i) its value minimizes towards brighter values of the image, whereas for the external nodes its value (IOD_e) is minimized towards low values (background).

The adjustment process consists of minimizing these energy functions, considering a global energy as the sum of the different energy terms, weighted with the different exposed parameters, as used in the optimizations with a greedy algorithm (Ansia et al., 1999) or with an evolutionary approach (Ibáñez et al., 2009; Novo et al., 2011).

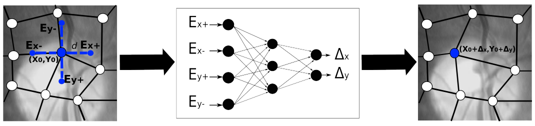

Figure 1: Diagram of the shift production for a given TAN node using the ANN.

2.2 Artificial Neural Networks for the Image Segmentation

A new segmentation technique that uses Artificial Neural Networks (ANNs) to perform the optimization of the Topological Active Nets is proposed in this work. In particular, we used a classical multilayer perceptron model that is trained to know how the TAN nodes have to be moved and reach the desired segmentations.

The main purpose of the ANNs consist of providing, for a given TAN node, the most suitable movement that implies an energy minimization of the whole TAN structure. This is not the same as the greedy algorithm, which determines the minimization for each node movement. All the characteristics of the network were designed to obtain this behavior, and are the following:

Input. The ANN is applied iteratively to each of the TAN nodes. The network has as input the four hypothetical energy values that would take the mesh if the given node was moved in the four cardinal directions. Moreover, these values are normalized with respect to the energy in the present position, given the high values that the energy normally takes, following the formula:

$$E_i' = (E_i - E_c)/E_c \tag{4}$$

where E_i is the given hypothetical energy to be normalized and E_c is the energy with the TAN node in the present location.

Hidden Layers. One single hidden layer composed by a different number of nodes. The sigmoid transfer function was used for all the nodes.

Output. The network provides the movement that has to be done in each axis for the given TAN node. So, it has two output nodes that specify the shift in both directions of the current position.

These characteristics can be seen in Figure 1. In this case, we obtain the values of the hypothetical energies that would be taken if we move the central node in the x and y axes, represented by the E_{x-}, E_{x+}, E_{y-} and E_{y+} values. These are introduced as the input values in the corresponding ANN, that produces, in this example, a horizontal displacement for the given TAN node. This movement, provided by the network outputs, is restricted in a small interval of pixels around the current position, typically between 1 and 5 pixels in both axes and directions.

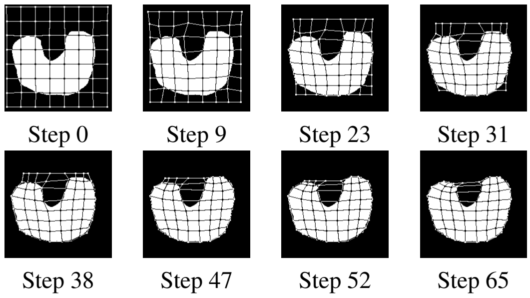

Figure 2: Emergent segmentation provided by the ANN in different steps.

Once we have the ANN correctly trained (with the evolutionary algorithm), we can use it as a “segmentation operator” that progressively moves the entire set of TAN nodes until, after a given number of steps, the TAN reaches the desired segmentation. In this process, the ANN is applied to each of the nodes sequentially. Such a temporal “step” is the application of the ANN to all the nodes of the TAN. An example of segmentation is shown in Figure 2, where the TAN was established initially in the limits of the image and all the nodes were moved until a correct segmentation was reached.

2.3 Differential Evolution for the Optimization of the Artificial Neural Network

Differential Evolution (DE) (Price and Storn, 1997)(Price et al., 2005) is a population-based search method. DE creates new candidate solutions by combining existing ones according to a simple formula of vector crossover and mutation, and then keeping whichever candidate solution which has the best score or fitness on the optimization problem at hand. The central idea of the algorithm is the use of difference vectors for generating perturbations in a population of vectors. This algorithm is specially suited for optimization problems where possible solutions are defined by a real-valued vector. The basic DE algorithm is summarized in the pseudo-code of Figure 3.

One of the reasons why Differential Evolution is an interesting method in many optimization or search problems is the reduced number of parameters that are needed to define its implementation. The parameters are F or differential weight and CR or crossover probability. The weight factor F (usually in $[0,2]$)

1. Initialize all individuals x with random positions in the search space
2. Until a termination criterion is met, repeat the following:
   - For each individual x in the population do:
     - 2.1 Pick three random individuals x_1, x_2, x_3 from the population they must be distinct from each other and from individual x.
     - 2.2 Pick a random index $R \varepsilon 1,...,n$, where the highest possible value n is the dimensionality of the problem to be optimized.
     - 2.3 Compute the individual's potentially new position $y = [y_1,...,y_n]$ by iterating over each $i \varepsilon 1,...,n$ as follows:
       - 2.3.1 Pick $r_i \varepsilon U(0,1)$ uniformly from the open range (0,1).
       - 2.3.2 If $(i = R)$ or $(r_i < CR)$ let $y_i = x_1 + F(x_2 - x_3)$, otherwise let $y_i = x_i$.
     - 2.4 If $(f(y) < f(x))$ then replace the individual x in the population with the improved candidate solution, that is, set $x = y$ in the population.
3. Pick the individual from the population that has the lowest fitness and return it as the best found candidate solution.

Figure 3: Differential Evolution Algorithm.

is applied over the vector resulting from the difference between pairs of vectors (x_2 and x_3). CR is the probability of crossing over a given vector (individual) of the population (x_1) and a vector created from the weighted difference of two vectors ($F(x_2 - x_3)$), to generate the candidate solution or individual's potentially new position y. Finally, the index R guarantees that at least one of the parameters (genes) will be changed in such generation of the candidate solution.

One of the main advantages of DE is that it provides an automatic balance in the search. As it was indicated (Feoktistov, 2006), the fundamental idea of the algorithm is to adapt the step length ($F(x_2 - x_3)$) intrinsically along the evolutionary process. At the beginning of generations the step length is large, because individuals are far away from each other. As the evolution goes on, the population converges and the step length becomes smaller and smaller.

2.3.1 ANN Genotypic Encoding

In our application, a single ANN was used to learn the movements that have to be done by the internal and the external nodes. In the evolutionary population, each individual encodes the ANN. The genotypes code all the weights of the connections between the different nodes of the ANN. The weights were encoded in the genotypes in the range $[-1, 1]$, and decoded to be restricted in an interval [-MAX_VALUE, MAX_VALUE]. In the current ANN used, the interval $[-1, 1]$ was enough to determine output values in the whole range of the transfer functions of the nodes.

We initialized the TAN nodes in the borders of the images and applied a fixed number of steps. Each step consists of the modification produced by the ANN for each of the nodes of the TAN. Finally, the fitness associated to each individual or encoded ANN is the energy that has the final configuration of the TAN which must be minimized. So, the fitness is defined only by the final emergent segmentation provided by an encoded ANN.

Moreover, the usual implementation of DE chooses the base vector x_1 randomly or as the individual with the best fitness found up to the moment (x_{best}). To avoid the high selective pressure of the latter, the usual strategy is to interchange the two possibilities across generations. Instead of this, we used a tournament to pick the vector x_1, which allows us to easily establish the selective pressure by means of the tournament size.

3 RESULTS

Different representative artificial and real CT images were selected to show the capabilities and advantages of the proposed method. Regarding the evolutionary DE optimization, all the processes used a population of 1000 individuals and the tournament size to select the base individual x_1 in the DE runs was 5% of the population. We used a fixed value for the CR parameter (0.9) and for the F parameter (0.9). These values provided the best results in all the images. In the calculation of the fitness of the individual, we applied a number of steps between 50 and 400, depending on the complexity and the resolution of the image.

Table 1 includes the energy TAN parameters used in the segmentation examples. Those were experimentally set as the ones in which the corresponding ANN gave the best results for each training.

Table 1: TAN parameter sets used in the segmentation processes of the examples.

Figures	*Size*	α	β	ω	ρ	ξ	δ	τ
4,5,6	8×8	1.0	1.0	10.0	4.0	0.0	6.0	30.0
7	12×12	0.0	2.0	20.0	3.0	0.0	5.0	0.0
9	8×8	4.5	0.8	10.0	2.0	7.0	20.0	40.0
10	8×8	4.5	0.8	10.0	2.0	7.0	20.0	40.0

3.1 Segmentation of Artificial Images

Firstly, we tested the methodology with artificial images with different characteristics. In this case, we used a training set of 4 artificial images, each one with different characteristics (different shapes, inclusion of

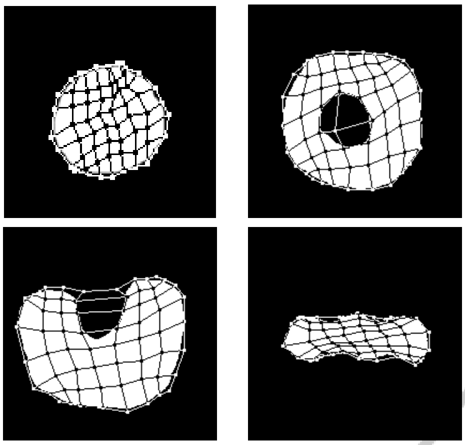

Figure 4: Results obtained with the best ANN for the segmentation of the training images.

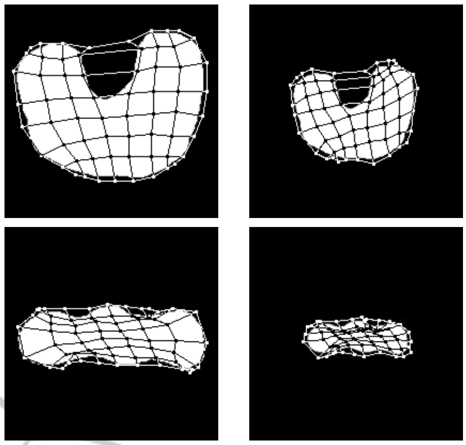

Figure 5: Results obtained when the best ANN is tested with scaled artificial objects.

concavities, holes, etc.). The fitness is defined as the sum of the individual fitnesses provided by the same ANN (individual) in all the training images.

Figure 4 shows the final segmentations obtained with the training set. Moreover, we tested the trained ANNs with a different set of images. Once we have the ANNs trained, the segmentation is fast and direct, applying the modifications to the TAN nodes a given number of steps until we reach the final segmentation. Note that two of the images have great difficulties for a perfect segmentation, with a big hole and a deep concavity, so some nodes can incorrectly fall in the hole or the concavity. For testing the trained ANN, we scaled and rotated a couple of difficult images of the training dataset, to verify the independence of the training regarding modifications in the used objects. Figures 5 and 6 show the final results with the test set of images. As the Figures show, the ANNs are able to reach correct results, which demonstrates that the ANN has learned to move correctly the nodes, independently of the training image or images used, to provide a final correct segmentation.

3.2 Comparison of the proposed Method and the Greedy Algorithm

We compared the proposed method with respect to the greedy approach previously defined. We selected a domain with real difficult images, as we segmented the optic disc in eye fundus images, as detailed in (Novo et al., 2009). The objective is the segmentation of the optic disc (oval bright area in the image) which also provides the localization of the center of the optic disc. As Figure 7 shows, the greedy local search falls in local minima quite fast, being impossible to reach the optic disc boundary (Figure 7 (a)). On the contrary, the ANN learned how to move all the nodes and was capable to reach an acceptable result (Figure 7 (b)–(d)). Note the capability of the evolved ANN to overcome the high level of noise, that prevents the correct segmentations by the greedy methodology.

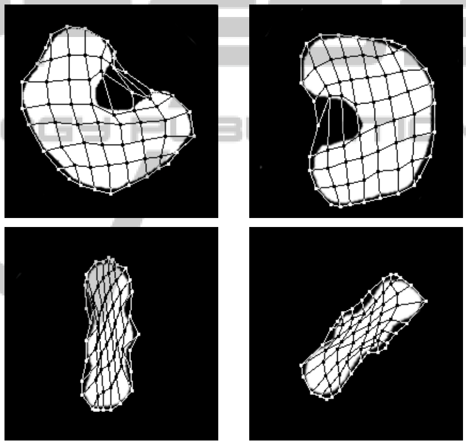

Figure 6: Results obtained when the best ANN is tested with rotated artificial objects.

In this case, additionally to the TAN energy parameters depicted in Table 1, we also used the ad-hoc energy terms designed for this specific task, as detailed in (Novo et al., 2009). These energy terms are “circularity”, that potentiates a circular shape of the TAN, and “contrast of intensities”, that tries to put the external nodes in locations with bright intensities in the inside and dark intensities outside. This term was designed to avoid the falling of the external nodes in the inner blood vessels. In this segmentation, the corresponding energy parameters of these two ad-hoc energy terms took values of $cs = 30.0$ and $ci = 15.0$, respectively.

To explain why the greedy local search and the

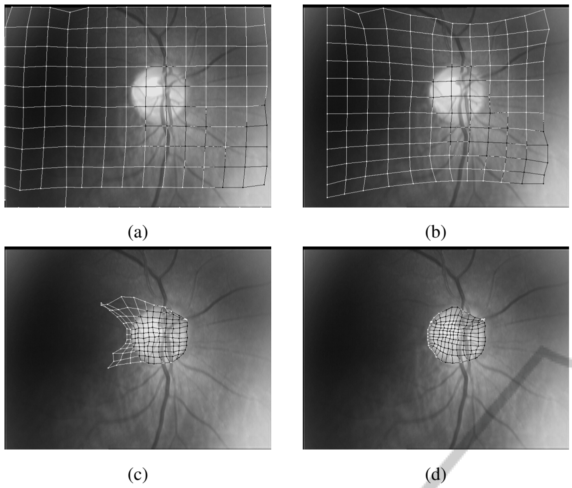

Figure 7: Comparison between the greedy algorithm and the proposed method. (a) Final result with the greedy approach. (b)–(d) Segmentation provided by the ANN in different temporal steps: 30, 171 and 399.

proposed method behave differently, we included, in Figure 8, a graphic with the percentage of the TAN node shifts that implied a maintenance or improvement (decrement) in terms of energy, and for each step in the segmentation of the optic disc of Figure 7. In the graphic, the main difference between the proposed method and the greedy local search is clear. Using the greedy method, all the movements of the TAN nodes imply a new position with an energy at least the same as the previous one, and better if possible (100% in the graph). That is why, in this particular segmentation, the greedy method falls in local minima, because the nodes cannot find a better position in the neighborhood and in few steps. However, with the proposed method, the ANN learned to produce "bad" movements (an average of 50% at the final steps), that implied worse energies in the short term, but they were suitable to find a correct segmentation in terms of the entire segmentation process.

3.3 Segmentation of Real Images

Moreover, as in the case with artificial images, we trained the ANNs with a given set of medical CT images, and after that, we tested the method with a different dataset. We selected a set of images that included objects with different shapes and with different levels of complexity. The CT images correspond to a CT image of the head, the feet, the knee and a CT image at the level of the shoulders. The images used in the testing correspond to CT images of the same close areas, but with a slightly different shape and with deeper concavities. All these CT images presented some noise surrounding the object, noise that was introduced by the capture machines when obtaining the medical CT images.

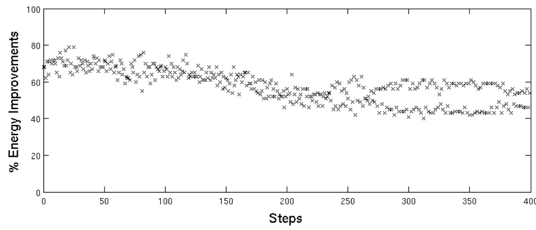

Figure 8: Percentage of TAN node movements with an energy maintenance or improvement, over the temporal steps, and using the trained ANN in the segmentation of Figure 7.

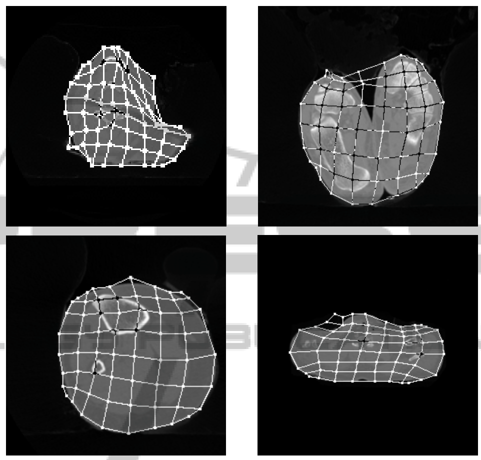

Figure 9: Results obtained with the best evolved ANN and the training set of real CT images.

Figure 9 includes the final segmentations with the training dataset, whereas Figure 10 details the final segmentations obtained with the best trained ANN and the test set of images. In both cases, the evolved ANN was capable to provide acceptable results, including a correct boundary detection and overcoming the presence of noise in the images.

Again, in the difficult parts of the images, like the concavities, some external nodes fall incorrectly in the background. This can be improved changing the energy parameters, increasing the TAN energy *GD* (Gradient Distance), but it deteriorates other objectives like smoothness. So, the energy parameters are always a compromise to obtain acceptable results in different kind of images.

4 CONCLUSIONS

We proposed a new methodology for image segmentation using deformable models. We used Topological Active Nets as extended model which integrates features of region-based and boundary-based segmenta-

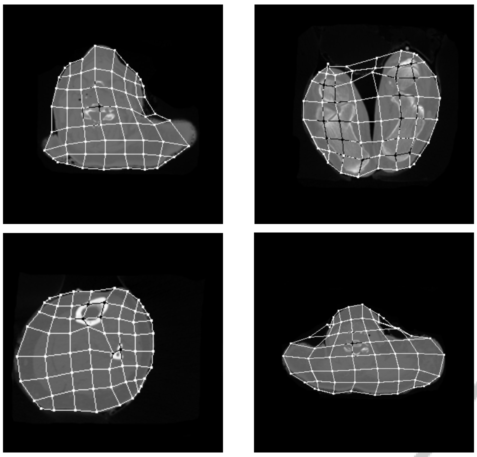

Figure 10: Results obtained with the best evolved ANN and the test dataset of real CT images.

tion techniques. The deformation through time was defined by an evolutionary trained ANN, since the ANN determined the movements of each one of the nodes. The process was repeated for all the nodes and in different temporal steps until the final segmentation was obtained.

Thus, the ANN provides an "emergent" segmentation, as a result of the local movements provided by the ANN and the local and surrounding energy information that the ANN receives as input. The methodology was proved successful in the segmentation of different artificial and real images, and overcoming noise problems. Moreover, we tested the ANN, trained with a set of images, with different testing images, obtaining acceptable results. So, our trained ANNs can be considered as "segmentation operators".

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