Efficient Object Extraction Using Fuzzy Cardinality Based Thresholding and Hopfield Network

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Abstract

An efficient technique that integrates the advantages of both fuzzy theory and Hopfield type neural network for object extraction from noisy background is proposed in this article. In the initial phase of the proposed technique, a fuzzy contrast enhancement of the input noisy object scene is carried out. Subsequently, the object scene is thresholded based on its fuzzy cardinality values to generate a smaller region of interest (ROI). Finally, a Hopfield network is used in the ROI to extract the object from the noisy background. Since the estimated ROI is lesser in size than the entire object scene, the Hopfield network required for the object extraction has a smaller network configuration. This in turn makes the object extraction process more efficient rather than the conventional approach where a fully connected network, with number of nodes equal to the number of pixels in the object scene, is used.

1. Introduction

Extraction and detection of objects from a noisy background [1, 2, 3] is by itself a subject of interest in the field of image processing and computer vision. Both classical and fuzzy set theoretic approaches are in use for the purpose of object extraction [4, 5]. Researchers have also relied upon the neural networking approaches for object extraction because of their properties of massive parallelism, adaptability, ability to learn and graceful degradation in case of component failure [6, 7]. A neural network, which comprises a collection of processing elements, i.e. neurons, along with their interconnections, forms the basis of such decision making systems. The operation of a neuron is determined by a transfer function that defines the neurons' output as a function of the input signals. Every connection entering a neuron has an adaptive coefficient, called weight, assigned to it. The weight determines the interconnection strength between neurons, and it can be changed by a learning rule that modifies the weight in response to the input signals and the value supplied by the transfer function. Various neural network models, differing in their structural details, are described in the literature. Some popular techniques for object extraction employ Hopfield [8, 9, 10], Kohonen self-organizing feature map [11] and the adaptive resonance theory (ART) [12].

There have been several attempts to fuse the merits of fuzzy set theory and artificial neural networks under the heading of *neuro-fuzzy computing* for improving the performance of the decision-making systems with regard to the problem of object extraction and detection. Huntsberger and Ajjimarangsee [13] modified the Kohonen feature map into a fuzzy self-organizing feature map. Fuzziness was also incorporated into the learning process by replacing the learning rate with fuzzy membership of the nodes of each class. Further modifications in this direction as to the termination condition and rate of learning have been reported in Bezdek et al [14]. Carpenter et al. [15] developed a fuzzy version of the ART by designing a neural network structure, which minimizes predictive error and improves generalization. Previous attempts employing the Hopfield model for object extraction [16, 17] were centered on utilizing a fully connected Hopfield network over the entire object scene, with each neuron connected to its neighboring neuron. Such a network, upon stabilization, led to the detection and extraction of objects. However, the inherent problem with this network was in the large number of interconnections used.

In this paper, we propose an efficient technique to reduce the network configuration of a Hopfield network used for object extraction. Instead of using a fully connected network configuration over the entire image, a smaller region of interest (ROI) is extracted from the object scene and the network is employed within this ROI. For this, a fuzzy estimation of the object scene is employed and a thresholding based on the fuzzy cardinality values of the object scene is used to extract the region of interest (ROI). Subsequently, a Hopfield type network that assumes each pixel in the region of interest as a node, thus having a reduced architecture is used to extract the object.

2. Object Extraction

In this section, we first provide the basic concepts of fuzzy theory, followed by a detailed description of the proposed object extraction methodology.

2.1 Basic Concepts in Fuzzy Sets

A fuzzy set A in a space of points $U = \{x\}$ is a class of events with a continuum of grades of membership and is characterized by a membership function $\mu_A(x)$. This membership function associates with each point $x \in U$, a real number $\mu_A(x)$in the interval [0,1], with the value of $\mu_A(x)$ representing the grade of membership of x in A. The resolution of a fuzzy set A is determined by the α*-cut* of the fuzzy set, which is a crisp set A_α that contains all the elements of the universal set U that have a membership grade in A greater than or equal to α, i.e.,

$$A_\alpha = \{x \in U | \mu_A(x) \geq \alpha\}$$

for$\alpha \in [0, 1]$. If

$$A_\alpha = \{x \in U | \mu_A(x) > \alpha\}$$

then A_α is called a *strong* α*-cut*. The set of all levels $\alpha \in [0, 1]$ that represents distinct α-cuts of a given fuzzy set A is called a level set Λ_A of A i.e.

$$\Lambda_A = \{\alpha | \mu_A(x) = \alpha, \text{ for some } x \in U\}$$

2.2 Proposed Methodology

The entire procedure leading to the task of object extraction has been accomplished in three phases as follows:

2.2.1 *Contrast Enhancement*

In this phase, the noisy object scene (A) is fed as input and contrast enhancement is done by means of the fuzzy contrast intensification operation INT(A), proposed by Zadeh [1972], as follows:

$$INT(A) = \begin{cases} 2\mu_A(x)^2; & 0 \leq \mu_A(x) \leq 0.5 \\ 1 - 2[1 - \mu_A(x)^2]; & 0.5 \leq \mu_A(x) \leq 1 \end{cases}$$

2.2.2 *Extraction of the region of interest*

Similar to the cardinality of a crisp set, which is defined as the number of elements in a crisp set, the *cardinality* (or *scalar cardinality*) of a fuzzy set A is the summation of the membership grades of all elements of x in A. It is given by

$$|A| = \sum_{x \in U} \mu_A(x)$$

where U is the universe of discourse. The relative cardinality of A is

$$|A|_{rel} = \frac{|A|}{|U|}$$

where |U| is finite. The relative cardinality evaluates the proportion of elements of U having the property A when U is finite. When a fuzzy set A has a finite support, its cardinality can be defined as a fuzzy set. This fuzzy cardinality is denoted by $|A_f|$ and is defined by Zadeh as

$$|A_f| = \sum_{\alpha \in \Lambda_A} \frac{\alpha}{|A_\alpha|}$$

where α is the cut-off value, A_α is the α-cut of the fuzzy set (A) and $\Lambda_A$is the corresponding level set. In this phase, an estimation of the fuzzy cardinality of the object scene is carried out on the resultant intensified object scene. In this process, the entire object scene is sampled by a window ($\Re$) and the fuzzy cardinality ($A_f(\Re)$) is estimated over this window as

$$|A_f(\Re)| = \left[\sum_{\alpha \in \Lambda_A} \frac{\alpha}{|A_\alpha|} \right]_{\Re}$$

The object scene is then thresholded based on the average of the fuzzy cardinality values. These operations lead to a smaller region of interest in the object scene.

2.2.3 *Object Extraction using Hopfield Network*

The ROI obtained in the previous phase is fed as an input to a Hopfield network (see figure 1) with first order connectivity, which considers each pixel as a neuron.

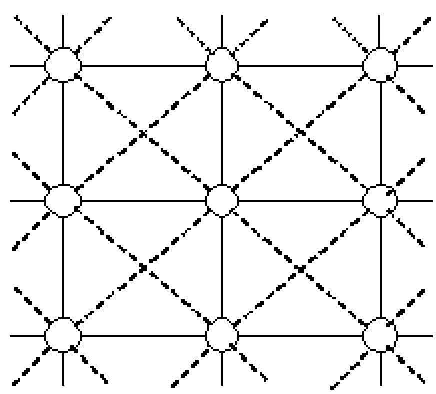

Figure 1: Topology of Hopfield network with first order connectivity (dotted lines show second order connectivity)

The essence of the object-background classification task is to differentiate between the different energy levels corresponding to the object and the background. The energy function for this model has two parts. The first part is due to the local field or the local feedback and the second part is due to the input bias of the neurons. In terms of the gray levels of the images, the first part is due to the impact of the gray levels of the neighboring pixels, whereas the second part is due to the gray value of the pixel under consideration. The Hopfield network extracts the object by minimizing the energy (E) given by

$$E = -\sum_i \sum_j W_{ij} V_i V_j - \sum_i I_i V_i$$

where the first part is the total energy contributed by all the pixel pairs and the second part is the contribution due to the input bias values of the individual pixels. V_i, V_j are the status of the i^{th} and j^{th} neurons, respectively and W_{ij} is the connection strength between these two neurons and I_i is the initial input bias to a neuron.

3. Results

The effectiveness of the proposed technique has been demonstrated using a synthetic image (figure 2a and 2b) and a real life spanner image (figure 2c), all of size 128 x 128. Various levels of noise with zero mean and standard deviation of σ were added to the images. The objects with different noise levels are shown in figures (3), (4) and (5). The extracted objects for different noise levels, with the fully connected network architecture with first order connectivity and the evolved network architecture are shown in figures (6), (7) and (8). For a fully connected Hopfield network architecture using first order connectivity employed on a 128x128 image, the number of connections are 128x128x4 = 65536. Tables 1, 2 and 3 show the number of connections and % reduction in the number of connections for the evolved Hopfield network with reduced architecture using first order connectivity for different noise levels viz. σ = 8, 10 and 12 for the synthetic images and the spanner image, respectively. It is evident from the tables that a significant % reduction in the network is obtained.

To evaluate the image quality of the extracted object, we have computed the percentage of correct classification (pcc) of pixels as

$$pcc = (tcc \times 100)/(m \times n)$$

where, tcc is the total number of pixels correctly classified for an (m x n) image. It is noted that for the synthetic image1, the pcc of the extracted images by the full and the reduced Hopfield network is same (99.14%) for noise level of σ = 8. However, for the other values of σ, an improvement in the pcc values is obtained using the reduced network over that of the full network. For example, with σ =10 and 12, the pcc values for the reduced network are 98.19% and 94.89% respectively, while those for the full network are 98.14% and 94.75% respectively. For the synthetic image2, the pcc values are same viz. 97.81% and 97.19% for noise level of σ=8 and 10 with both the reduced and the full network. However, there is an improvement in the pcc value with the reduced architecture (94.31%) as against that with the full architecture (94.16%) for noise level of σ=12. For the spanner image, although the pcc are same (97.03% and 96.36% respectively) for both the networks using σ = 8 and 10, for σ = 12, an improvement in pcc value with the reduced architecture (95.40%) is observed as compared to that with the full architecture (95.25%). The improvement in the pcc values can be attributed to the fact that a substantial amount of noise is removed during the process of extraction of the ROI using the fuzzy cardinality based thresholding.

Table 1: Reduced architecture for the synthetic image1

Noise Levels	Number of connections	% reduction in number of connections
$\sigma = 8$	29504	54.98
$\sigma = 10$	29824	54.49
$\sigma = 12$	32192	50.88

Table 2: Reduced architecture for the synthetic image2

Noise Levels	Number of connections	% reduction in number of connections
$\sigma = 8$	26560	59.47
$\sigma = 10$	27008	58.79
$\sigma = 12$	29312	55.27

Table 3: Reduced architecture for the spanner image

Noise Levels	Number of connections	% reduction in number of connections
$\sigma = 8$	9536	85.45
$\sigma = 10$	10304	84.28
$\sigma = 12$	13568	79.30

4 Conclusions

In this article we have proposed a technique that exploits the advantages of both fuzzy set theory and Hopfield type network for object extraction from a noisy background. The effectiveness of the proposed fuzzy cardinality based thresholding method in order to evolve Hopfield type neural network with lesser number of nodes has been demonstrated for two synthetic images and a real life spanner image with different noise levels. Even though the resultant architecture is found to be much smaller as compared to that with the maximum number of interconnections, the quality of the extracted object obtained by the reduced architecture is improved or remains the same as that obtained by a fully connected architecture with the maximum number of nodes. As a scope for further work, it may be investigated whether the architecture of the ROI-based network may be reduced further by using sophisticated optimization tools. The advantages foreseen in this direction are two-fold: firstly, a reduced network implies faster processing, and secondly, the generalization capability is expected to improve up to a certain level, resulting in better quality of the extracted object. Moreover, there is a scope of integrating the two phases of thresholding and extraction into a single phase by using the fuzzy information in the Hopfield network itself. The authors are currently working in this direction.

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References

[1] R. C. Gonzalez and P. Wintz. *Digital Image Processing, Reading*. MA: Addison-Wesley, 1977.

[2] J. C. Bezdek. *Pattern Recognition with Fuzzy Objective Function Algorithms*. New York: Plenum Press, 1981.

[3] A. Rosenfeld and A. C. Kak. *Digital Picture Processing*. New York: Academic Press, 1982.

[4] Ching-Teng Lin and C. S. George Lee. *Neural Fuzzy Systems* New Jersey: Prentice Hall P T R, 1995.

[5] S. K. Pal and D. D. Majumder. *Fuzzy Mathematical Approach to Pattern Recognition*. New York: John Wiley (Halsted Press), 1986.

[6] J. J. Hopfield and D. W. Tank. Neural computation of decisions in optimization of problems. *Biol. Cybern*, 52:141-152, 1985.

[7] D. E. Rumelhart, J. McClelland and P. D. P. research group. *Parallel Distributed Processing: Explorations in the Microstructure of Cognition*. Cambridge, MA: MIT Press, 1986.

[8] J. J. Hopfield. Neural network and physical systems with emergent collective computational abilities. *Proc. National Academy of Science, USA*, 79:2554-2558, 1982.

[9] J. J. Hopfield. Neurons with graded response have collective computational properties like those of two state neurons. *Proc. National Academy of Science, USA*, 3088-3092, 1984.

[10] S. Munshi, S. Bhattacharyya and A. K. Datta. Photonic Implementation of Hopfield Neural Network for associative pattern recognition. *Proc. SPIE.*, 4417:558-562, 2001.

[11] T. Kohonen. *Self-Organization and Associative Memory*. Berlin: Springer-Verlag, 1989.

[12] R. P. Lippmann. An introduction to computing with neural nets. *IEEE ASSP Magazine*, 3-22, 1987.

[13] T. L. Huntsberger and P. Ajjimarangsee. Parallel self-organizing feature maps for unsupervised pattern recognition. *Int. J General Systems*, 16:357-372, 1990.

[14] J. C. Bezdek, E. C. Tsao and N. R. Pal. Fuzzy Kohonen Clustering Networks. *Proc. 1st IEEE Intl. Conference on Fuzzy Systems, San Diego, CA*, 1035-1043, 1992.

[15] G. A. Carpenter, S. Grossberg, S. Markuzon, N. Reynolds and D. B. Rosen. Fuzzy ARTMAP: a neural network architecture for incremental supervised learning of analog multidimensional maps. *IEEE Trans. Neural Networks*, 3:698-713, 1992.

[16] S. K. Pal, S. De and A. Ghosh. Designing Hopfield type networks using genetic algorithms and its comparison with simulated annealing. *Intl. J. of Pattern Recognition and Artificial Intelligence*, 11:447-461, 1997.

[17] A. Ghosh, N. R. Pal and S. K. Pal. Object background classification using Hopfield type neural networks. *Intl. J. of Pattern Recognition and Artificial Intelligence*, 6:989-1008, 1992.

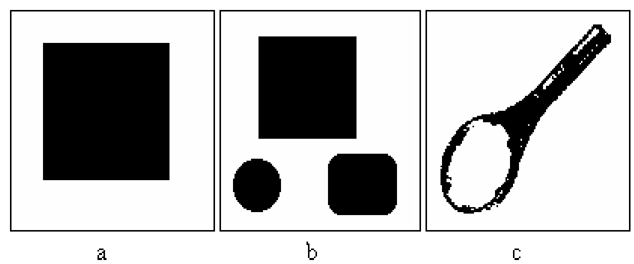

Figure 2: Original Images

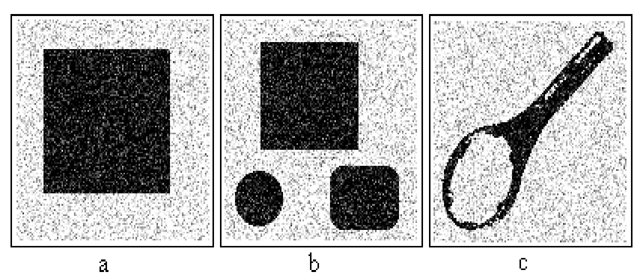

Figure 3: Objects with different noise levels (a)(b)(c) Images at σ=8

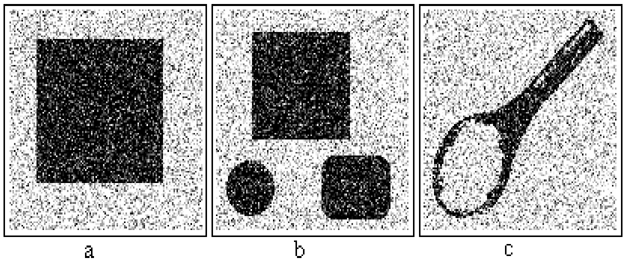

Figure 4: Objects with different noise levels (a)(b)(c) Images at σ=10

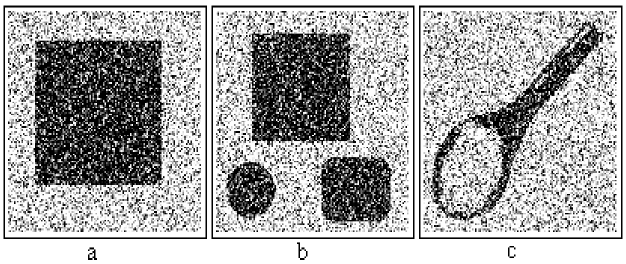

Figure 5: Objects with different noise levels (a)(b)(c) Images at σ=12

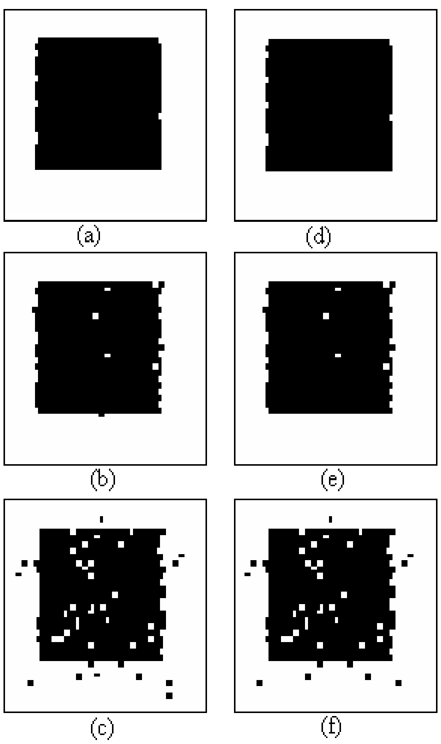

Figure 6: Object extraction at different noise levels (a)(b)(c) Outputs using fully connected network (d)(e)(f) Outputs using evolved network

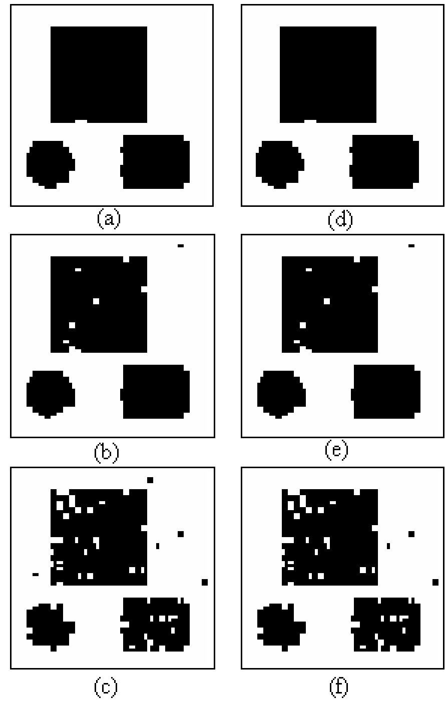

Figure 7: Object extraction at different noise levels (a)(b)(c) Outputs using fully connected network (d)(e)(f) Outputs using evolved network

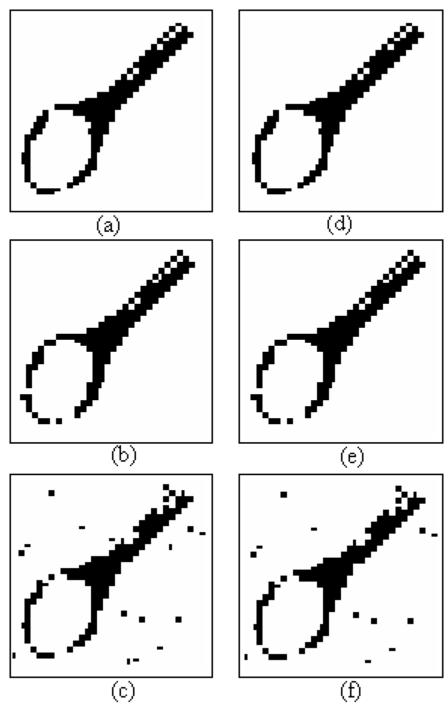

Figure 8: Object extraction at different noise levels (a)(b)(c) Outputs using fully connected network (d)(e)(f) Outputs using evolved network