International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online)) Volume 2, Issue 2, Feb 2014)

Applying Reduced Coulomb Energy Neural Network for Removal of Image Noise

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Abstract: **Training neural network plays an important role in image processing when a neural network is used for removal of image noise. There has been a deep relationship between image processing and neural network. Several kind of neural networks used to solve different image processing problems. This paper describes usability of Reduced Coulomb energy (RCE) neural network to remove image noise by creating clusters training patterns. Also we briefly describe the RCE neural network.**

Keywords: **RCE neural network, image processing, classifier.**

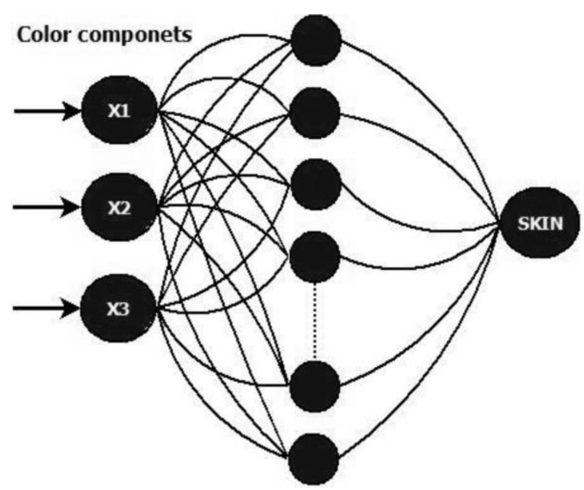
I. Introduction

The RCE algorithm is a well known method used for classification task. It is based on incremental modification of a neural network structure. RCE neural network identified as a supervised pattern classifier used on behalf of the estimation of feature region. The RCE is one of the first incremental models of neural networks. In this model decision unit are characterized by their influence region, defined by a hypersphere around the unit, whose radius is equal to the threshold of the unit. The state spsce is then divided into zones, each dominated by different decision units. New units are created with an initial chosen radius if a presented template does not fit into one of the influence regions of the units associated with the correct class. On the other hand, redii associated to units belongings to a wrong class but whose influence region include the presented pattern are lowered to avoid this situation.

The most important advantage resides in the simplicity of the algorithm and its ability to modify the number of units. The decision regions are built with respect to a threshold associated to each decision units. The algorithm has only to decide whether a new point belongs to an existing class and, in this case, if it is correctly classified. Then the decision of creation of a new decision unit is taken according to the result of this comparison. A new decision unit defines a new hypersphere whose centre coordinates are chosen as the actual input prototype.

II. Network Structure

The RCE neural network is a supervised learning scheme for estimating and classifying feature regions, which has three layers: the input layer, the prototype layer, and output layer. For the neural network architecture, there are full connections between each layer. In our system, this three-layer structure arrangement is illustrated in Fig.



Architecture of RCE neural network

III. RCE Learning

RCE neural network is a supervised pattern classifier used for the judgment of feature area. It provides a way of region modification that is middle among Parzen-window and K-nearest-neighbor. Parzen window uses fixed window size where K-nn uses variable window size. Throughout the network training, the size of the hyperspherical window is in sync in orientation to the adjacent point of a diverse class in feature space. The feature region of each class is enclosed by generated hyperspherical prototypes. It is not desirable to straight use RCE neural network for the supervised segmentation. The major disadvantage of RCE learning is the necessity of a whole sample set for every classes.

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In order to segment the object of concern from the image environment, it requires the samples of both the object and the image environment. However, it is not practical to get the sample of the image environment when the image environment randomly changes over the time. One more disadvantage is that all prototypes are generated by means of the set size in one class, which is not precise and efficient for region estimation.

The learning algorithm of the RCE net is:

1. Set the maximal radius Rmax of hyperspheres.
2. Allocate a the first hidden neuron and set its weight vector to be equal to the first input vector of the training set (w1=x1) and set its radius to Rmax(center and radius of the first hypersphere). Connect the output of this hidden neuron (with weight v1=1) to the output neuron that represents corresponding class y1. Clear a modify variable (mod:=False) and set a pointer to the second vector of the training set.
3. Calculate Hamming distances between the current input vector xm and centers of all hyperspheres (wj weights); if some distances are less than or equal to the radius (dj & Rj) the corresponding hidden neurons become active. Following three situations may occur:

(a) All active hidden neurons represent (sub) category of the current input vector. Nothing is done in this case. Go to 4).

(b) Some of active hidden neurons belong to the same class as current input but the others belong to the other class(es). Reduce radiuses of all active hidden neurons (hyperspheres) that are associated with incorrect classes until they become inactive; set the modify variable (mod: =true).

(c) No hidden neuron is active. Allocate a new hidden neuron with weight vector wj_{new}= xm and with maximal radius R_{max} (center and radius of new hypersphere). Connect its output (with weight vij_{new}=1) to the corresponding or new output neuron I (that represents class y_m). Set the modify variable (mod: =true).

4. If the next input vector in the training set exists then set a pointer to this vector and go to 3).
5. If mod=False then stop the learning process else set a pointer to the first input vector of the training set, clear the modify variable (mod: =False) and go to 3).

Recall of the RCE net is very easy:

1. Calculate Hamming distances between the input vector x and the centers of all hyperspheres (wj weights); if some distances are less than or equal to the radius (dj__Rj_) the corresponding hidden neurons fire and their output values z_j become 1(all other hidden neurons hold zero output values).
2. Calculate output values yi of each output neuron as a logical *or* function of its binary inputs.

1. Network Training

Suppose that the number of training data are m, which can be expressed as **X** = {**x**1, **x**2, ..., **x**i, ..., **x**m}. The i^{th} training sample consists of three color elements, where **x**i = [Yi,Cbi,Cri]T. Once the training sample is transmitted to the prototype layer, the Euclidean distances d(**x**i,**C**j) between the training sample and existing neuron centers are calculated. Equation 2 represents the distance between the i^{th} training signal **x**i and jth each prototype neuron center.

$\mathbf{C}^j$.

$$d(\mathbf{x}_i, \mathbf{C}^j) = \sqrt{(Y_i - C^j_Y)^2 + (Cb_i - C^j_{Cb})^2 + (Cr_i - C^j_{Cr})^2}.$$

If d(**x**i,**C**j) < Rj , it means that the xi falls into the jth neuron. In this case, the corresponding counter Nj in **P**j will increase by 1. On the other hand, if the **x**i does not fall into any existing prototype cells, a new prototype neuron **P**(n+1) = [Cn+1Y ,Cn+1Cb ,Cn+1Cr ,Rn+1,Nn+1]T with center at [Yi,Cbi,Cri]T will be added in this layer. Then, the prototype density is computed. The essence of prototype density is that the neurons are adequate for typifying skin color clustering distributions, only if the corresponding prototype densities are larger than a pre-defined threshold.

Otherwise, this neuron will be discarded. The density of the prototype neuron is computed by:

$$D_{\mathbf{P}^j} = \frac{3N^j}{4\pi {R^j}^3}.$$

Based on the Euclidean distance evaluation and prototype density, the framework of the traditional RCE neural network can be constructed as shown in algorithm .

Algorithm 1: the conventional RCE neural network training method:

1. set prototype radius Rj = r (for every j)
2. while this is the first iteration or no more prototypes are detected in the last iteration do

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3. for i = 1 to m (all training samples) do
4. if the the pixel is not labeled then
5. for j = 1 to n (all existing neurons) do
6. calculate d(xi,Cj) by equation 2
7. if d(xi,Cj) _ Rj then
8. increase Nj by 1, nominate xi belongs to Pj
9. jump out of for loop
10. end if
11. end for
12. if xj does not fall into any existing neurons then
13. create a new neuron Pn+1 centered at xi with
14. radius r, and Nj = 1
15. end if
16. end if
17. end for
18. for j = 1 to n (all existing neurons) do
19. calculate density value by equation 3
20. if density value is beyond a threshold _d then
21. retain the cell Pj and label all the training data in
22. Pj as j
23. else
24. discard Pj and regard all the training data in Pj as unlabeled
25. end if
26. end for
27. end while

2. Training Reduced Coulomb Energy Networks

Adjust each radius to be as large as possible (up to a maximum) without containing point from another category

For each training sample xj, j=1,..,n set radius.

Algorithm 2: RCE Training algorithm

1. Begin initialize j $\leftarrow$0, n $\leftarrow$ # pattern, ϵ $\leftarrow$ small param, λm $\leftarrow$max radius
2. do j $\leftarrow$ j + 1
3. wij $\leftarrow$ xi (train weight)
4. X^ $\leftarrow$ arg min D(X, X') (find nearest point not in ωi) x$\notin$ ωi
5. λj $\leftarrow$ min [D(X^,X') - ϵ, λm] (set radius)
6. if X ϵ ωk then ajk $\leftarrow$ 1
7. until j = n
8. end

III. Classification With Reduced Coulomb Energy Networks

Classification methods can be implemented to classify the entirety scene content into a partial number of main classes.

Classification with the trained RCE network is fairly trouble-free in principle. As shown below basic classification algorithm, that works well to classify items using neural network approach.

Algorithm 3: RCE Classification

1. begin initialize j$\leftarrow$0, k$\leftarrow$ test pattern, D $\leftarrow$ {}
2. do j $\leftarrow$ j + 1
3. if D (x, xj') < , λj then D $\leftarrow$ D1 U xj'
4. until j = n
5. if label of all xj'ϵ D, is the same then return label of all xk ϵ Dt
6. else return "ambiguous" label
7. end

IV. Conclusion And Future Work

Reduced Coulomb energy (RCE) neural network is a supervised pattern classifier. Throughout the network training, the size of the hyper spherical window is attuned in reference to the adjacent point of a dissimilar category in feature space. A Reduced Coulomb Energy Network is useful tool for generating trained pattern. In Redial Basis Function neural network (RBFNN) we used Gaussian based kernel function. The RCE algorithm produces a trained pattern for the removal of image noise. In that procedure the dissent factor of noise is raise and the target PSNR value is achieved. As recognized, the high-order statistical connection does play a significant part in image filtration method area. So in order to take advantage of the high-order statistical connection amongst variables, so we used RCE algorithm for training the network.

In future we will try to use Reduced Coulomb energy (RCE) neural network and its other variants like RCE-1, RCE-2, and RCE-3 with wavelet transform to generate efficient training pattern for image noise removal.

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