INTUITIONAL CLASSIFICATION OF AERIAL IMAGES

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Abstract

Raster databases has been using widespreadly in geographic information system (GIS) technology. As known GISs are useful tools for managing the spatially related information.

Aspect of mapping and city planning management of GIS systems has vital important for managing quite a few spatially related information.

Ortophoto raster-based GISs graphic databases supplies a lot of information, provided by their raster databases. But this informations are not available efficently because of nongraphic database restrictives.

In this study, an unextractable information is extracted via artificial intelligence, for example, the total joint pixel area of gardens and parks. Extractable informations has topological defined relations between graphic and nongraphic databases in classical GIS.

I. RADIAL BASIS FUNCTION NETWORKS (RBFNs)

RBFNs are general purpose networks which can be used for a variety of problems including: System Modeling, Prediction, Classification. Use an RBFN in most situations in which you consider using a back-propagation network. In general, an RBFN is any network which makes use of radially symmetric and radially bounded transfer functions in its hidden layer.[1].

Radial basis networks may require more neurons than standard feed-forward backpropagation networks and often they can be designed in a fraction of the time it takes to train standard feed-forward networks. They work best when many training vectors are available [2].

PNN and GRNN could both be considered RBFNs. In RBF training the first phase of training the network is a clustering phase and in this phase, the incoming weights to the prototype layer learn to become the centers of clusters of input vectors. When the clustering phase finishes, the radii of the Gaussian functions at the cluster centers are set using a 2 Nearest Neighbor procedure.

In table 1, some radial basis functions, using in RBFNs, mathematical forms are described.

Multiquadratik	$(1+z)^{\frac{1}{2}}$
Cauchy	$(1+z)^{-1}$
Inverse Multiquadratik	$(1+z)^{-\frac{1}{2}}$
Gaussien	$e^{\frac{-x^2}{\beta^2}}$

Table 1: Radial Basis Functions in RBFNs.

The radius of a given Gaussian is set to the average distance to the two nearest cluster centers. At this point, the mapping layer is trained using one of a selection of error learning rules. Some softwares are allows a hidden layer between the prototype layer and the output layer for richer mappings, for example Matlab's Neural Network Toolbox and Neuralware Professional Plus/II.

Advantage of RBFNs are,

·Trains faster than a claassical gradient decenting back-propagation network.

·Leads to better decision boundaries than classical back-propagation algorithms when used for classification and decision problems.

·Potentially flags radical, new data as presented to the network and disadvantages of RBFNs are,

·The initial learning phase of radial basis function networks is an unsupervised clustering phase. Important discriminatory information could be lost in this phase.

·Regression problems may require unbounded transfer functions to be efficiently solved.

·Back-propagation can give a more compact distributed representation.

II. TRAINING PHASE and RBFNs ARCHITECTURE

For realizing the aim of this study we processed an image via RBFNs (Radial Basis Neural Network –RBFNs- and Probabilistic Neural Network-PNNs-) and extracted classified images. In additionally RBFN's and PNN's classification performances are also compared.

Training patterns are captured from original image, given at figure 2.

The training patterns are 20x20 sized images and illustrated at figure 1 at bellow.

-a-

1st training subset patterns

-b-

2nd training subset patterns

-c-

3th training subset patterns

Figure 1 : -a-, -b- and –c- are represents training subsets. Each subset is expresses an independent class and this subsets are member of the main training set.

Figure 2 : Total area of investigation.

The parameters used in RBFNs are illustrated in figure 3, given at below. Additionally *Extended Bar Delta Bar Delta* (EDBD) [3] learning rule and sigmoidal transfer function used in hidden 2 layer of RBFNs. At the end of the training process RMS 0.0786 and Correlation 0.9496 obtained when RMS not change any more.

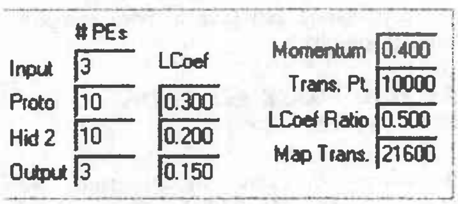

Figure 3 : Paramethers of RBF ANNs.

The RBFNs interpretation of Figure 2 is given at Figure 4 and the sub-band images are expressed at figure 6.

Figure 4 : RBFNs Interpretation of Figure 2. (Joint image of each three class)

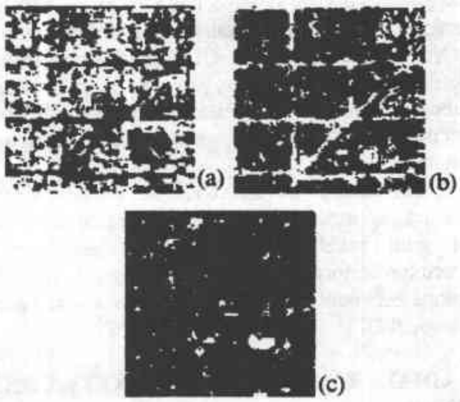

Figure 6 : Sub-band images of Figure 4, produced by Radial Basis Neural Network.

(a) represents 135 610 pixel as green areas, (b) expresses 76 372 pixel as roads and (c) represents 26 348 pixel as building frameworks.

Figure 7 is expresses the Probabilistic Neural Network's (PNNs) architecture, used for Figure 8.

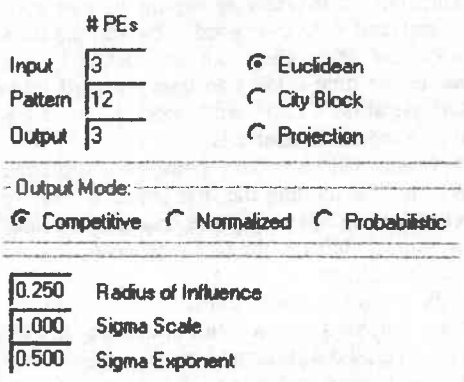

Figure 7 :PNNs Architecture used for Interpretation of Figure 2.

Figure 8: Probabilistic Neural Network's Interpretation of Figure 2.

136.262 pixels is belong to green areas. The Crosswise Correlation matrix is given at below. This matrix is ameasure of success of classification of Figure 2 via PNNs.

$$\underline{M_{corr}} = \begin{bmatrix} 0.0000 & 0.0139 & 0.5275 \\ 0.0003 & 0.9814 & 0.4542 \\ 0.9997 & 0.0046 & 0.0183 \end{bmatrix}$$

III.RESULTS AND CONCLUSIONS

Classification is a useful tool for information extracting from aerial images and artificial intelligence is effective tool for this aim. Because of artificial neural networks (ANNs) inherit abilities these tools supply exciting abilities for image processing such as classification. This study is exposed that ANNs are very suitfull tools for image interpretation.

IV. REFERANCES

1. Neural Computing, A Technology Handbook for Professional II/PLUS and NeuralWorks Explorer, Pittsburgh: NeuralWare, Inc., Technical Publications Group, 1996.
2. Matlab 5.3. Neural Network Toolbox, Users Guide, January 1998 Fifth Printing Version 3. Mathworks Inc.
3. NeuralWorks Professional II/PLUS Supplement version 5.3, 1997, page 40.