MRF-MBNN: A Novel Neural Network Architecture for Image Processing

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Abstract. Contextual information and a priori knowledge play important roles in image segmentation based on neural networks. This paper proposed a method for including contextual information in a model-based neural network (MBNN) that has the advantage of combining a priori knowledge. This is achieved by including Markov random field (MRF) into the MBNN and this novel neural network is termed as MRF-MBNN. Then the proposed method is applied to segmenting the images. Experimental results indicate the MRF-MBNN is superior to the MBNN in image segmentation. This study is a successful attempt of incorporating contextual information and a prior knowledge into neural networks to segment images.

1 Introduction

Although neural networks have been extensively studied in the field of image segmentation, two challenging problems should be further studied, which are the excellent incorporation of contextual information and the inclusion of a priori knowledge [1].

The main features of the model-based neural network (MBNN), over traditional neural networks, are that inclusion of (global) a priori knowledge in the network, combination of a priori knowledge and adaptive learning, and exclusion of combinatorial explosion that is inherent in other existing methods of modeling intellect and, in particular, performing automatic recognition [2], [3], [4]. For its features, especially the advantage of combining a priori knowledge, the MBNN was attempted to segment the images [5]. The contextual information, however, was not incorporated in the literature.

Markov random field (MRF) is a very popular method for image modeling and plays an important role in image analysis. It has the advantages of the ability to catch contextual information and tractable computation [6], [7], [8]. Therefore, in this paper, we introduce MRF into the MBNN to segment the images and use the term MRF-MBNN for this novel network. To decrease the computation burden, we employ the technique of preassigning a class number [5]. The experimental results show a significant improvement over the MBNN. We conclude that the reason is that contextual information, that is, neighborhood information, is incorporated in the MRF-MBNN, which is not included in the MBNN.

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2 MBNN

The MBNN, in this paper, is based on the maximum likelihood adaptive neural system (MLANS) proposed by Perlovsky [9]. It has all the available information as its input, including the observed values $\mathbf{X}_n$, a priori knowledge and environmental interrogation feedback, if available. The output contains the estimated parameters of all classes defined as follows:

$$N_{km} = \sum_{n=1}^{N} W_{nkm} \ . \tag{1}$$

$$\mathbf{M}_{km} = \sum_{n=1}^{N} \frac{W_{nkm}\mathbf{X}_n}{N_{km}} \ . \tag{2}$$

$$\mathbf{C}_{km} = \sum_{n=1}^{N} \frac{W_{nkm}\left(\mathbf{X}_n - \mathbf{M}_{km}\right)^T \left(\mathbf{X}_n - \mathbf{M}_{km}\right)}{N_{km}} \ . \tag{3}$$

where W_{nkm} is the weight of the network, N_{km} is the estimation of object numbers of each type, $\mathbf{M}_{km}$ is the estimation of mean vector of each type, and $\mathbf{C}_{km}$ is the covariance matrix of each type; k is the class of objects, m is the type of the objects within the class.

If all available information is determined by probability terms, the weights are defined as posteriori Bayesian probabilities as follows:

$$W_{nkm} = P\left(k,m|n\right) = \mathrm{pdf}\,(\mathbf{X}_n|k,m) \Big/ \sum_{k',m'} \mathrm{pdf}\,(\mathbf{X}_n|k',m') \ . \tag{4}$$

where $\mathrm{pdf}\,(\mathbf{X}_n \mid k,m)$ is a probability density function (pdf).

A Gaussian mixture model is used in this paper, thus the total pdf for all observations $\{\mathbf{X}_\mathrm{n}, n=1,...,N\}$ is a product of individual pdf($\mathbf{X}_n$).

$$\mathrm{pdf}\left\{\mathbf{X}_n, n=1,\ldots,N\right\} = \prod_{n=1}^{N} \mathrm{pdf}\,(\mathbf{X}_n) \ . \tag{5}$$

$$\mathrm{pdf}\,(\mathbf{X}_n) = \sum_{k=1}^{K}\sum_{m=1}^{M} \mathrm{pdf}\,(\mathbf{X}_n|k,m) \ . \tag{6}$$

$$\mathrm{pdf}\,(\mathbf{X}_n|k,m) = (2\pi)^{-d/2}(\det \mathbf{C}_{km})^{-1/2} \exp(-\tfrac{1}{2}\mathbf{D}_{nkm}\mathbf{C}_{km}^{-1}\mathbf{D}_{nkm}^T) \ . \tag{7}$$

$$\mathbf{D}_{nkm} = \mathbf{X}_n - \mathbf{M}_{km} \ . \tag{8}$$

3 MRF-MBNN

Because MRF models express global statistics in terms of the local neighborhood potentials, most approaches have used MRF to accurately model the unknown images. And most of these are distinguished by the choice of potential function that assigns cost to differences between neighboring pixels.

Here we model the image X by the Gaussian MRF (GMRF) with a symmetry neighboring η, then X can be written in terms of a non-causal autoregressive (AR) representation with correlation coefficients θ [10],

$$X_s = \sum_{r \in \eta_s} \theta_r X_{s+r} + e_s \ . \tag{10}$$

$$B_\theta X = e \ . \tag{11}$$

where B_θ is a $M \times N$ matrix (M, N is the width and height of the image X respectively), and e is a zero mean Gaussian noise process with autocorrelation given by

$$E[e_s e_{s+r}] = \begin{cases} \sigma^2 & if \quad r = (0,0) \\ -\theta_r \sigma^2 & if \quad r \in \eta_s \\ 0 & otherwise \end{cases} \ . \tag{12}$$

where σ is a parameter that controls scale or variation in X.

It is possible, without loss of generality to halve the number of correlation parameters by making $\theta_r = \theta_{-r} \ \forall r \in \eta_s$. In addition, the parameter set θ should satisfy $1 - \theta^T \phi_s > 0 \ \ \forall s \in \Omega$, and ϕ_s is a vector whose length is equal to the number of neighboring pixels η_s, which is defined by

$$\cos\left[\begin{pmatrix} \frac{2\pi s_1}{M} & \frac{2\pi s_2}{M} \end{pmatrix} \begin{pmatrix} r_1 \\ r_2 \end{pmatrix}\right] \quad r \in \eta_s \ . \tag{13}$$

This condition can guarantee the positive definiteness of covariance matrix of X. If the covariance matrix of e is $\sigma^2 B_\theta$, and that of X is $\Sigma = \sigma^2 B_\theta^{-1}$ [10]. Then the joint probability density functions of X is

$$p(X = x) = \frac{\sqrt{\det B_\theta}}{(2\pi\sigma^2)^{MN/2}} \exp\left\{ -\frac{1}{2\sigma^2} x^T B_\theta x \right\} \ . \tag{14}$$

Also the conditional distribution for a single pixel may be written [10],

$$p(x_s \mid x_t, \forall t \neq s, t \in \Omega) = p(x_s \mid x_{s+r}, r \in \eta_s)$$
$$= \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{ -\frac{[x_s - \sum_{r \in \eta_s} \theta_r x_{s+r}]^2}{2\sigma^2} \right\} \ . \tag{15}$$

This is a variation of the GMRF. Now we make an attempt to introduce GMRF into the MBNN. If we assume that the conditional distribution for every pixel belonging to some class k in the image satisfies the following forms:

$$p(x_s \mid x_t, k) = \frac{1}{\sqrt{2\pi\sigma_k^{\ 2}}} \exp\left\{ -\frac{\left[(x_s - \mu_k) - \sum_{r \in \eta_s} \theta_r (x_{s+r} - \mu_k) \right]^2}{2\sigma_k^{\ 2}} \right\} . \tag{16}$$

where μ_k is the mean parameter.

As we know, the weights W_{nk} in the MBNN are defined as follows (here we take account of the class k, not the type m):

$$W_{nk} = p(k \mid X_n) = \frac{p(X_n \mid k)}{\sum_{k'} p(X_n \mid k')} . \tag{17}$$

Thus when MRF is incorporated in the MBNN, the weights should be modified,

$$\begin{aligned} W_{nk} &= p(k \mid X_n, X_t) \\ &= \frac{p(X_n, X_t \mid k)}{\sum_k p(X_n, X_t \mid k)} = \frac{p(X_t \mid k) p(X_n \mid X_t, k)}{\sum_k p(X_t \mid k) p(X_n \mid X_t, k)} . \end{aligned} \tag{18}$$

$$p(X_n \mid k) = \sum_t p(X_n \mid X_t, k) p(X_t \mid k) . \tag{19}$$

these equations above are the basis for the design of the novel neural network named as MRF-MBNN.

To estimate the correlation coefficients θ, we adopt the modified version of the EM algorithm [11], which is an iterative procedure for approximating maximum-likelihood estimates. At each iteration, two steps are performed: the expectation step and the maximization step. Because iterations also exist in the MBNN, this modified version of EM algorithm can be applied to the estimation of MBNN parameters.

4 Results and Discussions

To decrease the computational burden, in all the experiments, the technique of preassigning a sufficiently large class number k_0 is used to adaptively determine the real class number k.

The Lena image is presented for segmentation (Fig. 1(a)). First of all, we employ the MBNN to segment the image. After 5 iterations, the MBNN convergences and the

(a) (b) (c)

Fig. 1. (a) original image; (b) segmentation results by using the MBNN. The number of iterations is 5. k_0=40, k=20; (c) segmentation results by using the MRF-MBNN. The number of iterations is 3. k_0=40, k=4

segmentation results are shown in Fig. 1(b). Obviously the segmentation performance is poor and many details of the images are not well segmented. Does the selection of the preassigned class number k_0 or the number of iterations correspond to the poor performance? We repeated all the experiments after changing the preassigned class number and increasing the number of iterations. However, the results indicated our efforts are in vain and were almost the same as the previous ones (data not shown). Since neighborhood pixel values of the image are highly correlated, we consider that the fact that contextual information is not incorporated in the MBNN for segmentation maybe results in the poor performance.

Then we apply the MRF-MBNN proposed in this study, which well combines the MBNN and MRF and solves the problem of no contextual information existing in the MBNN, to segment the images. After three iterations, the network is in convergence and the results are shown in Fig. 1(c). Obviously, the results obtained by using the MRF-MBNN are superior to the previous ones obtained by using the MBNN. We consider that the proposed method takes account of the total interactions between all the pixels and their neighboring pixels, which results in better segmentation performance. The fact indicates that incorporating contextual information through MRF actually improves the performance of segmentation.

5 Conclusions

In this paper, we combine the MBNN with MRF and propose a new neural network termed MRF-MBNN. It well incorporates contextual information and a priori knowledge into neural networks, which exist in traditional neural networks. To test its performance, the segmentation experiments by using the MBNN are carried out as control experiments. The results indicate that the MRF-MBNN is actually superior to the MBNN and gives a good performance in segmentation. This study provides a novel approach to successfully incorporate contextual information and a prior knowledge into neural networks to segment images.

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