HALFTONE/CONTONE CONVERSION USING NEURAL NETWORKS

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ABSTRACT

A novel neural network based method for halftoning and inverse halftoning of digital images is presented. We first start from inverse half-toning of images produced from error diffusion methods using a RBF Network plus a MLP network. The restored contone images have had good quality already. Then, a SLP neural network is used to refine the halftoning processing and the training process of the inverse half-toning network is also involved. The combined training procedure produces half-tone images and the corresponding continuous tone images at the same time. It is found that these contone images have even better PSNR performance. Furthermore, the resulted half-tone images are visually sharper and clearer, too. The proposed inverse half-toning method is also compared to the well-known LUT method.

1. INTRODUCTION

Halftoning technology is mainly applied in the fields of printing devices and image displays. It is a process of transforming continuous tone (also called contone) images to half-tone images when the devices can only process bi-level images. The challenge still lies in how to produce a high quality image that is visually close to its original through bi-level devices. Many well-known halftoning technologies can be found in [1]-[2]. Among them, dithering and error diffusion are two mostly used approaches. Because error diffusion methods generally have better visual quality, this paper will only focus on error diffusion based methods.

Another interesting question is how to convert halftone images back to the corresponding contone images [1]. Because resolution of image scanners is higher and higher today, conversion of a scanned halftone image to a contone image becomes necessary. For inverse halftoning technology, many good studies are available in the literature, such as low pass filtering, POCS, logical filtering, iterative filtering, etc [11]-[12]. A Look Up Table (LUT) based algorithm proposed by M. Mese and P.P. Vaidyanathan [3] produces very good results. Further improvement can be seen in [4].

The research starts from inverse halftoning of halftone images produced by error diffusion method. The error diffusion based methods generally involves multiplication, summing and thresholding operations to produce a bi-level image. Theoretically, errors produced with error diffusion will be confined to a limited range in image space. Furthermore, each pixel of the halftone image contains the information of its physically adjacent pixels of the corresponding contone image. Therefore, the proposed RBF based inverse halftoning method uses 25 (a 5x5 area) halftone pixels to reconstruct the gray level of the center pixel. The RBF network is followed by an edge-based post-processing multi-layer perceptron (MLP). The proposed method requires much more computation than the LUT method, but it needs less amount of memory to store the system parameters. PSNR performances produced by these two methods are close to each other. However, the test halftone images are produced by simple Floyd method and the quality is not very good. If the halftoning can be improved, it is possible that the reconstruction quality can also be improved. There are other better halftoning methods such as [10]. However, both halftoning and inverse-halftoning may perform better if these two can be considered at the same time. In [10], human visual system (HVS) is used to evaluate the performance of a halftoning operation. Because neural network is known for its ability to approximate nonlinear functions through appropriate training procedure, it is possible to design a halftoning neural network and combine it with the RBF inverse halftoning network to result in even better performance.

In this paper, a single-layer perceptron halftoning network (SLP) is used to replace the simple Floyd error diffusion method. At the first training stage, the initial configuration of this SLP is set to perform the identical function of the Floyd error diffusion kernel. The RBF based network is trained for inverse halftoning with original contone images as the teaching samples. After the RBF network is well-trained, the halftoning SLP is also involved in the second training stage while training of the RBF continues. It is found that not only the PSNRs of the reconstructed contone images are improved, the visual quality of the corresponding halftone images produced by the halftoning SLP network is better than the original Floyd method. The combined training procedure stops

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when both networks converge. More detail will be disclosed in the later part of this paper.

The paper is organized as follows. The inverse halftoning RBF based neural network and the halftoning SLP network are introduced in section 2 and section 3, respectively. Section 4 illustrates the combination of these networks. In section 5, computer simulation results are presented. Conclusions and future works are given in section 6.

2. RBF BASED INVERSE HALFTONING NEURAL NETWORK

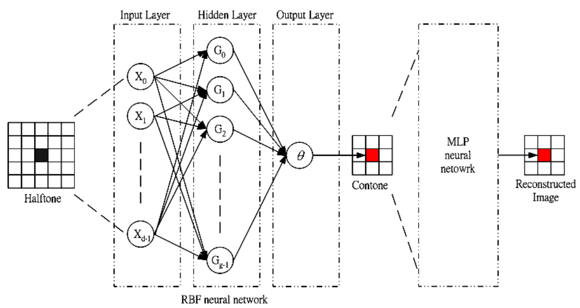

Fig. 1 RBF+MLP neural network mapping.

RBF and MLP neural network is clearly explained in [9]. Due to the regional characteristics of error diffusion methods, it is natural to consider RBF networks for inverse halftoning for RBF networks are generally good for interpolation, localized relationship exploration, universal nonlinear approximation, and blind source separation [9]-[10]. RBF network comprises an input layer, a hidden layer and an output layer. Its network architecture is shown in Fig. 1. The number of input neurons is d . The number of neurons in the hidden layer is g . There is only one output neuron. The RBF network can be expressed as $f_{RBF}: R^d \to R$. Furthermore, each hidden neuron is a multivariate gaussian function, as expressed in Eq(1):

$$G(X, X_i) = \exp(-(2\sigma_i^2)^{-1}\|X - X_i\|^2)\ , \forall i \in [0, g) \qquad (1)$$

where σ_i is variance, $X_i \in R^d$ is mean vector, and $X \in R^d$ is the input value for the *i-th* neuron. The network is fully connected and the output can be expressed:

$$O = \sum_{i=0}^{g-1} W_i G(X, X_i) - \theta\ , \forall i \in [0, g) \qquad (2)$$

where W_i denotes the synaptic weight associated with the *i*-th hidden. θ denotes the bias term of the output neuron. According to Fig. 1, the black point represents the center position of a $m \times m$ image block. The RBF network uses input halftone values of the image block to calculate the gray level of the center pixel and thus the whole contone image. In the RBF network, there are four sets of free parameters to be adjusted, namely X_i , σ_i , w_i and θ . Error signal, e , and cost function, E , are defined in Eq(3). Let N be the number of training samples, and j be the corresponding index. The training rules are written as:

$$E = \frac{1}{2}\sum e^2 \quad \text{, where} \quad e = (output) - (destination) \qquad (3)$$

$$\frac{\partial E}{\partial \theta} = \sum_{j=0}^{N-1} e_j \qquad (4)$$

$$\frac{\partial E}{\partial W_i} = \sum_{j=0}^{N-1} e_j \cdot G(X_j, X_i) \qquad (5)$$

$$\frac{\partial E}{\partial \sigma_i} = (-1)\sum_{j=0}^{N-1} e_j \cdot W_i \cdot \sigma_i^{-3} \cdot G'(X_j, X_i) \cdot (X_j - X_i)^T (X_j - X_i) \qquad (6)$$

$$\frac{\partial E}{\partial X_i} = \sum_{j=0}^{N-1} e_j \cdot W_i \cdot G'(X_j, X_i) \cdot \sigma_i^{-2} \cdot (X_j - X_i) \qquad (7)$$

To speed up the training, Resilient Propagation (RPROP) proposed by Riedmiller and Braun is applied [6]. In Fig.1, a MLP network for post-processing is added to improve the performance. Because this is just an ordinary MLP [9], we won't reiterate the detail in this paper.

3. SLP HALFTONING NEURAL NETWORK

In Floyd-Steinberg error diffusion methods [2], error caused by the thresholding operation will be diffused to the pixels processed later. In fact, this is equivalent to a SLP network with only one output neuron. The activation function of the output neuron is a hard-limiting function to perform the thresholding operation. However, a supervised training algorithm requires teaching signals. Because there are no "optimal " halftone images used as teaching signals, difficulties of training such a network do exist. However, since we have had good results with the proposed RBF based inverse halftoning technique, the performance may be even better if both the RBF and the SLP can be trained at the same time. Thus, original contone images can be used as our training samples.

The SLP network is configured as follows. The synaptic weight associated with the target pixel is always 1 and c is its gray level. ε_q is the difference between c and the output level, f_q . If the 4[th] order Floyd-Steinberg filter is used, the coefficients are $1/16$, $5/16$, $3/16$, $7/16$ and 1 . To have better results, the filter order can be increased.

The activation function has to be differentiable if Back-Propagation algorithm is used to train SLP networks [9]. To solve this problem, Noise Back-Propagation algorithm proposed by Wilson and Rock is adopted [5]. The activation function is replaced by the logistic function combined with a random noise generator in the training stage. At the testing stage, the activation function is still a hard-limiting function. They have proved that the types and sizes of the noises are not critical in most situations. The synaptic weight, w_i , used in the SLP network needs to be updated recursively. The training procedure also involves the RPROP algorithm to speed up the convergence.

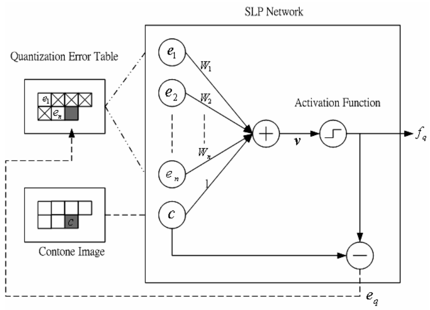

Fig. 2 Single Layer of FF Neural Network

Error signal, e, and cost function, E, are defined in Eq(3). The logistic function, $f = f_q$, is defined in Eq(8). v is defined as $v = \sum w_i \varepsilon_i + c$ and a denotes the slope parameter of the logistic function. ε_i's are the input from the network. The basic update rule is in Eq(9). Due to limited space of the paper, the detail training algorithm which combines noise back-propagation and Resilient Propagation (RPROP) will be presented in another paper.

$$f_q = \varphi(v) = [1 + \exp(-av)]^{-1} \tag{8}$$

$$\frac{\partial E}{\partial w_i} = \sum_{j \in N} a(f_q - d) f_q (1 - f_q) \varepsilon_i \tag{9}$$

4. HYBRID HALFTONE/CONTONE CONVERSION

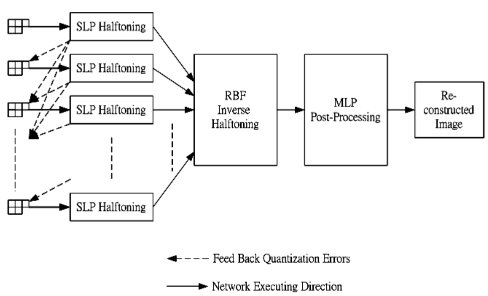

Fig. 3 Hybrid halftone/contone conversion network

Whereas halftoning SLP and inverse halftoning RBF perform reverse operations, we should be able to combine the two networks and train them together. The overall architecture is shown in Fig. 3. At the first stage, only the RBF network is involved in training procedure. The SLP network is set to the Floyd condition to produce halftone images and the parameters are not updated at this moment. After the RBF network training reaches its convergence, overall procedure goes into the second stage. At this stage, both RBF and SLP have to be trained. For SLP network, error signals are backward-propagated from RBF network. Therefore, the update rule has to be changed as:

$$\frac{\partial E}{\partial w_s} =$$

$$\sum_{j=0}^{N-1} \sum_{i \in g} e_j \cdot W_i \cdot G'(X_j, X_i) \cdot \sigma_i^{-2} \cdot (X_j - X_i)\ a \cdot \varphi_j \cdot (1 - \varphi_j) \cdot \varepsilon_s$$

where $\varphi_j = \left[1 + \exp(-a \cdot (\sum_s w_s \varepsilon_s)) \right]^{-1}$ (10)

The other processing is identical to those described in previous sections. As a result, the halftoning part will no longer be identical to the Floyd filter. We have increased the system order from 4 to 13.

5. EXPERIMENT RESULTS

Table 1 Comparison of different inverse halftoning methods

Halftone Color Image	LUT	RBF+MLP
Airplane	27.19 db	28.81 db
Pepper	26.16 db	27.85 db
Lena	27.92 db	31.32 db
House	26.56 db	28.02 db

10 color images obtained from [7] are used to be training samples. The PSNR results are shown in Table 1. Some important portions of reconstructed Lena image produced by LUT method and our method are shown in Fig.5 (c-1)~(c-4) and Fig. 5 (d-1)~(d-4), respectively. The proposed method achieves better PSNR performance, and the processed images are also smoother and clearer. Furthermore, corresponding portions of halftone Lena image obtained with standard error diffusion method [8] and SLP network are shown in Fig. 4 (a-1)~(a-4) and Fig. 4 (b-1)~(b-4), respectively. These images produced by SLP are visually also sharper and clearer. 20 other color images captured with a digital camera are used to test the PSNR performance of inverse halftoning. The average PSNR of these images is 29.23 db for RBF+MLP network, and 27.24 db for LUT method. Thus it can be seen that the neural network based method can provide good quality halftone and contone conversion.

6. CONCLUDING REMARKS

A neural based method for halftone and contone conversion is proposed. The combined training procedure for SLP network and RBF based network produces quality images. Though the computation complexity is higher than the well-known LUT method, the resulted contone images are smoother and constant PSNR improvement is also achieved. Furthermore, the resulted half-tone images are visually sharper and clearer. Though we have had good results on gray scale images, some color artifacts can be seen when this method is applied to color images. It is our future work to solve this problem.

7. REFERENCES

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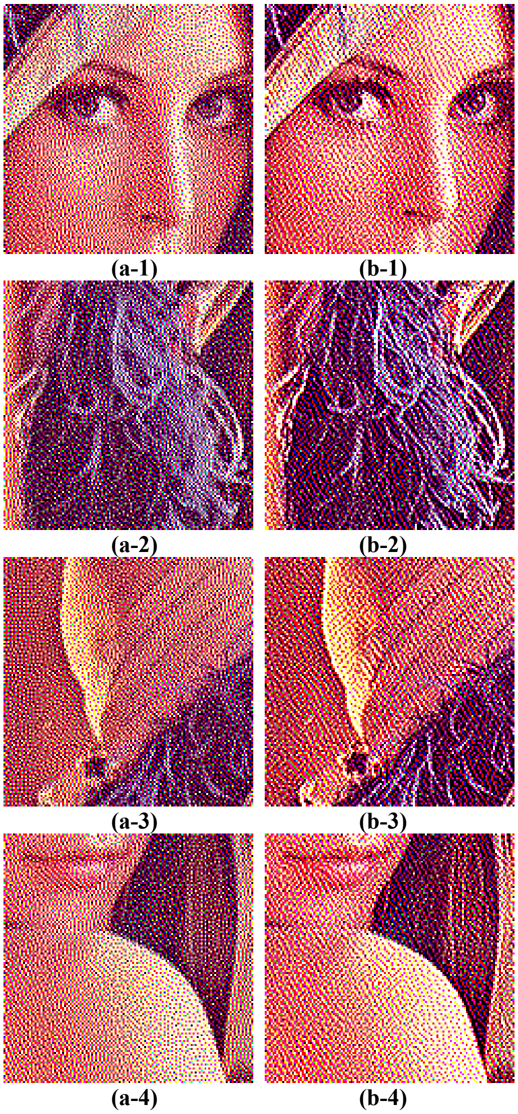

Fig. 4 "Lena" Halftone Images by Error Diffusion (a-1)~(a-4) and SLP (b-1)~(b-4)

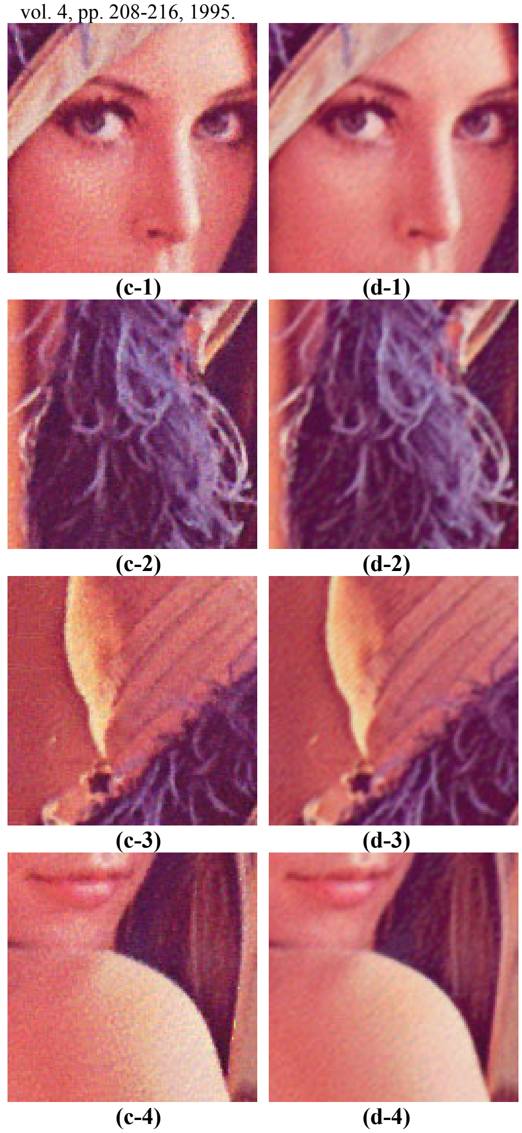

Fig. 5 "Lena" Contone Images by LUT (c-1)~(c-4) and RBF (d-1)~(d-4)