INVERSE HALFTONING FOR MONOCHROME PICTURES

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ABSTRACT

A class of inverse halftoning methods together with post-processing is proposed in this paper. In order to optimize the inverse operation of halftoning, we adopt the inverse modeling concept to find the least-squares solution of this problem. And then, the knowledge of image characteristics helps us in designing improved algorithms that produce the most promising pictures to our eyes. They are conceptually rather different from the traditional inverse halftoning methods that use simple low-pass filters. Furthermore, we develop a general space-varying sliding-window filter (SV-SWF) scheme. The goal is to be able to handle various types of pictures using the same basic inverse halftoning structure together with spatially adaptive parameters. This universal inverse halftoning operator is achieved by using an adequate classification scheme to separate image data into different groups, each corresponding to a set of pre-trained parameters. Due to the additional information in the inputs and the outputs utilized in our processing, better reconstructed images are obtained.

1. INTRODUCTION

Halftoning is a very popular technique for producing printed pictures with only two levels [1]. However, a number of image processing techniques such as filtering, enhancement, and compression are more efficient when they are performed on the gray-scale images. Therefore, the inverse halftoning technique that converts binary images to gray-scale images is important in practice applications. In addition, inverse halftoning can be used to monitor the printer outputs and thus can provide information for automatic calibration of printing process. To our knowledge, only a few inverse halftoning techniques have been published in the open literature [2-5]. A class of inverse halftoning methods together with post-processing is proposed in Section 2. Furthermore, we develop a general space-varying sliding-window filter (SV-SWF) scheme in Section 3. At the end, a concise conclusion summaries the major results in this paper.

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2. INVERSE HALFTONING USING INVERSE MODELING

The two popular classes of halftoning techniques that produce binary images are ordered dither and error diffusion. They differ in their processing structures and in the characteristics of the resultant binary images. Our goal is to find a general inverse halftoning method that can work with several different halftone techniques.

The two fundamental problems in halftoning, forward and inverse halftoning, can be viewed as image synthesis and image restoration problems respectively. In the problem of image restoration, an image has been degraded in some manner and the objective is to reduce or eliminate degradation. In this paper, halftoning, a nonlinear quantization operation, is viewed intentionally as a linear shift-invariant system with noise of specific distributions. This approach makes a number of systematic analysis methods possible.

2.1. General Inverse Halftoning System

Given a known halftoning method, the first step in designing the inverse halftoning method is to find a mathematical model using the relationship between the original gray-level images and the halftone images. Once we know the analytic model of halftoning, we can employ the known systematic methods to find the approximate functions which represent the inverse halftoning system. The method we choose is inverse system

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identification using adaptive signal processing techniques. The proper selection of inputs, outputs, and initial weights has a deciding influence on the performance. In general, reasonable performance can be achieved for typical image data.

2.2. Reconstruction Using a Sliding-window Filter (SWF)

The gray-scale images are reconstructed using a sliding window (FIR) filter. For each pixel location (x,y), we select a rectangular window S_{mn} centered around (x,y). In the training phase, weights of a sliding window filter W_{mn} are adjusted by the well-known LMS algorithm [6]. In the reconstruction phase, the reconstructed value is computed by linearly combining the halftone pixels in this window :

$$I_{xy} = \sum_{(k,l\in B)} \sum b_{kl} \, W_{kl}, \tag{1}$$

where b_{kl} represents the binary pixel and I_{xy}, the gray-level pixel. This procedure is repeated for every pixel in the image; hence, this window is slid across the image one pixel at a time (Figures 1 and 2).

2.3. Post-processing Using an Adaptive Low-pass Filter

When the SWF method is used for inverse halftoning, it is observed that there exist a few small *"lumps"— clusters of brighter and darker pixels—* on the reconstructed images. These "lumps" are generally of several pixels wide and appear randomly. They can not be removed by spatial-invariant low-pass filter because a low-pass filter with a lower cut-off frequency will produce excessive blurring on the resulting image. Note that median filters do not work well in this situation either because the residual noises here are made of small contiguous clusters rather than being impulsive. In order to remove these residual errors and to retain high quality gray-scale images, we apply a spatially adaptive post-processing algorithm that uses the local statistics. It is an improved version of the previously known algorithm [7].

For each pixel location (x,y), we take a small neighborhood (window) around (x,y). We then compute the mean μ as well as the standard deviation ν that characterizes locally the amount of variation among the pixels in this neighborhood. Then, the value of the center pixel (x,y) is modified according to the following rule :

$$\begin{aligned} \text{If } \nu \le K, \quad \text{then} \quad & I_{xy}^{new} = \mu + \left(\frac{\nu}{\nu + K}\right)\left(I_{xy}^{old} - \mu\right) \\ \text{else} \quad & I_{xy}^{new} = I_{xy}^{old} \end{aligned} \tag{2}$$

where the window size $= 5 \times 5$, and K is adjusted appropriately between 25 and 200. The superscripts "old" and "new" refer to the values of the pixel before and after adjustment, respectively. This operation is repeated over the entire image where the window is sliding across the image one pixel at a time. When the sliding window falls in a location that contains an edge or texture, the local variance tends to be larger than that of flat areas. This means that the value of a pixel is less likely to be adjusted when the content of the image block is complex. As a result, such an algorithm provides a smoothing operation without overly blurring an image.

3. UNIVERSAL INVERSE HALFTONING

Because of the nonlinear characteristics of halftoning systems whose operations depend on the local image property, a single spatial invariant sliding-window filter for inverse halftoning is limited by its structure in performance. When the content of an image window is complicated and is varying abruptly, such as edges, contours and texture areas, its local characteristics are very different from that in the flat areas. Hence, if we can design different inverse filters aiming directly at different types of image areas, we may obtain better recovered images. Instead of assuming the inverse halftoning system is a single linear system, the concept of a piece-wise linear system may be used. In this structure, adequate classification scheme which partitions data domain into segments (pieces) is very critical. It has a strong impact on the final recovered image quality.

What we plan to do is to find an appropriate method of classification that can separate image data into different groups for inverse halftoning purpose. This approach makes possible one single robust inverse halftoning scheme with groups of fixed parameters working on different types of image contents, and the goal of an universal inverse halftoning operator can thus be achieved. In other words, given an arbitrary halftone image, the best SWF weights can be found by table-look-up after classification, and the gray-scale image is reconstructed using this set of weights.

3.1. Reconstruction Using a Space-varying Sliding-window Filter (SV-SWF)

Instead of using a single fixed sliding-window filter in reconstruction, a more advanced technique, reconstruction using a space-varying sliding-window filter (SV-SWF), is proposed in this section. Compared to the previous assumptions of a single linear system, the concept of a piece-wise linear system may be closer to the ideal nonlinear inverse halftoning system. We expect that proper image classification technique and separate process aiming directly into different types of image areas can improve the recovered image quality mainly in non-flat areas and can reduce the algorithm sensitivity to data variation (different from training data).

The general SV-SWF inverse halftoning architecture is shown in Figure 3. The processing steps are summarized below.

1. Training phase:

   We partition the entire inverse halftoning system into several SWF subsystems. In this phase, we look for the best weights in each SWF subsystem based on the (classified) training data. A neighborhood window around pixel (x,y) is classified into one of the several pre-selected groups according to a specific classification scheme. And then, the neighborhood pixel windows belonging to the same groups together with their corresponding halftone values b_{mn}'s constitute the input/output pairs for designing the SWF subsystem using the LMS algorithm.

2. Reconstruction phase:

   To begin with, we first obtain $\hat{I}^1_{xy}$, a raw approximation of I_{xy}, by applying a spatial invariant SWF to the binary pixels centered at (x,y) and then obtain $\hat{I}^{1p}_{xy}$ by using post-processing described in Section 2. And then, a window $\hat{S}^{1p}_{mn}$ consisting of the reconstructed pixels around (x,y) is classified into one of the several groups according to the selected classification scheme. Once we know which group the pixel (x,y) belongs to, the corresponding sub-SWF weights can be found simply by table-look-up. Finally, the gray-scale image $\hat{I}^2_{xy}$ is reconstructed by multiplying the binary window B_{mn} with the chosen weights (SV-SWF). With another post-processing step, $\hat{I}^{2p}_{xy}$, produced from $\hat{I}^2_{xy}$, is often very close to the original gray-scale image I_{xy}.

3.2. Classification Schemes

In designing the space-varying sliding-window filter, an adequate classification scheme is very critical. It has a strong impact on the final recovered image quality. This classification problem will be studied using two types of processing algorithms: data local statistics and neural networks classification.

3.2.1. Local Statistics

When the sliding window shifts to the location that contains edges or texture, its local variance tends to be larger than that computed in the flat areas. What we need to do is to pre-select the number of partitioned groups and the local variance values that define the separation of groups. In our experiences, it is sufficient to merely partition data into three groups: low-variant, middle-variant, and high-variant regions. Many more classes provide little gain in PSNR. This is because pixels with similar characteristics can not be distinguished using just the first and second order statistics when, particularly, the local variance is large.

3.2.2. Neural Network Classification: Adaptive Resonance Theory Network - 2A (ART-2A)

Adaptive resonance architectures are neural networks that can perform stable classification for arbitrary sequences of input patterns. The ART-2A scheme [8] we use here is an efficient but simple neural net algorithm that can self-classify data patterns at fast learning rates. A new input pattern is classified into a certain category if it shares the same "invariant" properties of the data in that category. A parameter called the attentional vigilance parameter ρ determines how fine the classification is. If vigilance increases, then the system automatically searches for and learns finer recognition categories. That is, lower vigilance implies coarser grouping. The merits of the ART-2A classification scheme are that it is systematic and that its similarity criterion in classification is controllable in advance compared to those traditional pattern recognition methods. The classification criterion represents the similarity between an input pattern and the accumulated (network) internal groups. It uses the cosine of the angle between I, the normalization of input pattern, and z^*_j, the center of the jth group.

3.2.3. Universal Inverse Halftoning Operator Design

As described, we combine the schemes of data local statistics and the vector inner product comparison (ART-2A) to produce a high-performance classification algorithm for inverse halftoning. The effects of the data local statistics and the pattern recognition classification network ART-2A are complementary in this hybrid classification algorithm. When the local variance ν is smaller than a parameter K, the local variance ν dominates the final classification and decides directly which group the pixel belongs to. This is because a small local variance suggests that the corresponding pixel (x,y) usually locates in flat areas in our experiences. In this case, further classification does not help in improving the recovered image quality. However, when the local variance ν is greater than K, the classification network ART-2A dominates the final classification and decides which group it belongs to by calculating the vector inner product between the input pattern and the internal patterns. There, we proceed to more detailed classifying for the input pattern of which the corresponding pixel locates in the edges or texture areas. Confused by picking up most pixels in the flat areas, the weakness of reconstruction only using the pattern recognition classification network ART-2A can thus be overcome. In this way, we have successfully excluded the possibility of the mix-up in advance and assure the classification results produced from the ART-2A scheme suitable for our purpose. Therefore, the hybrid classification algorithm combining with the local variance separation in the first step and the ART-2A scheme for the high-variant pixels in the second step is generally well-performed.

4. SOME SIMULATION RESULTS

Thus far, we have constructed a multi-stagy solution to the inverse halftoning problem. Our reconstruction method often performs better than those of the known published inverse halftoning techniques. Comparing to the other known inverse halftoning methods, there are several features of our proposed methods. One is that the recovered image quality is superior to the other known methods. The other is that this method is robust which is almost independent of the content of the testing images. Furthermore, we are able to use a set of large-window weights in performing halftone image reconstruction. The measures in peak SNR (PSNR) of the proposed methods and some reported results are shown in Table 1.

4.1. Robustness

SWF Weights obtained from the training image perform very well on reconstructing the corresponding (training) halftone image. They do not perform as well on the other halftone images. However, although weights are strongly training-data dependent and also halftoning-technique dependent, universal weights can be found through proper selection of training image data. When such a set of universal weights are used on the outside-training halftone images, they usually have rather good performance in most cases. Our experimental results also show the known fact that most natural images have similar characteristics and most halftoning techniques perform in similar manners.

The SV-SWF weights obtained from the training image perform more effectively in reconstructing the halftone image than the SWF weights. They also perform as well on the out-side (training) halftone images. Although each subset of SV-SWF weights is strongly training data dependent, the performance in reconstruction using the universal set composed of subsets of SV-SWF weights are less data dependent. This is because each group contains image patterns of similar local characteristics that are less (entire) picture dependent.

4.2. Filter Size and Weights

Halftone images can usually be reconstructed satisfactorily using SV-SWF. Typically, a set of 7×7 sliding-window weights with vigilance parameter $\rho = 0.86$ has a better performance than a set of a smaller-size sliding-window with lower vigilance parameter. The optimal reconstructed images are always produced using the filter size from 7×7 to 9×9 when the other parameters kept invariant. To further reduce computational complexity, a 5×5 sliding-window is appropriate in producing good quality pictures.

5. CONCLUSION

In this paper, we analyze the relationship between the original gray-level images and the halftone images and propose successfully a set of inverse halftoning schemes. From the least-square solutions to the experimental neural networks solutions, we combine the inverse system identification techniques together with the image post-processing techniques and the adequate classification methods to improve the reconstructed image quality. The general space-varying sliding-window filter (SV-SWF) is successfully developed for inverse halftoning. This enables the goal of the universal inverse halftoning operator being achieved. Indeed, the simulation results show that these integrated algorithms produce better reconstructed images than any other known algorithms both in PSNR and in subjective evaluation.

6. ACKNOWLEDGE

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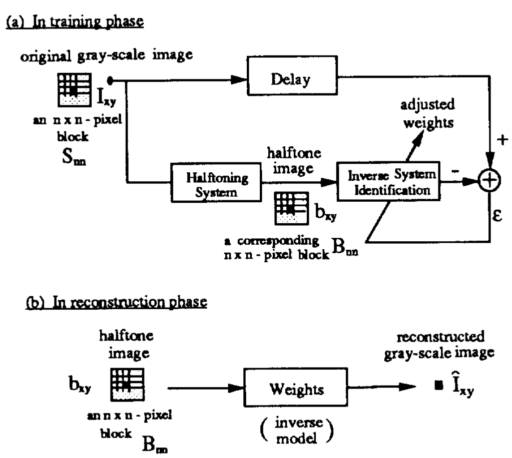

Figure 1: Reconstruction using a sliding-window filter

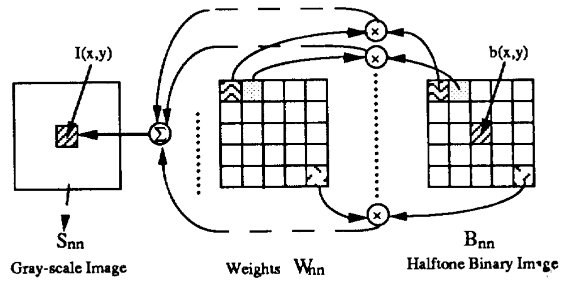

Figure 2 : Multiple-input one-output adaptive linear combination

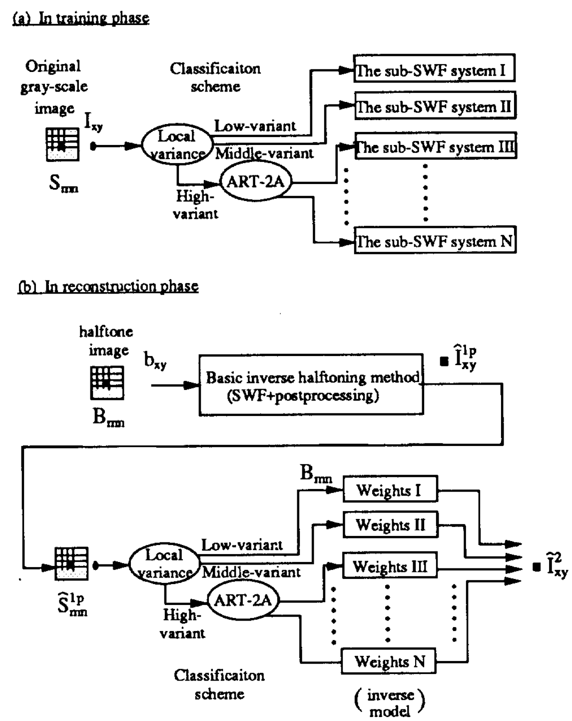

Figure 3 : General SV-SWF inverse halftoning system based on ASP and image classification

Schemes \ PSNR (dB)	Test images: Lena	Pepper	Jet
Miceli, 1992 [2]	19.89	*	*
Analoui, 1992 [3]	28.64	*	*
Wong,1993 [4]	31.9	30.3	*
Ting,1993 [5]	30.71	*	*
SWF	31.23	30.87	30.64
SWF + Post-processing	31.78	31.22	31.34
SV-SWF	32.77	32	32.17

Table 1 : The performance comparison