Error Diffused Halftohe Classification using Stochastic Geometrical Features

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***Abstract*—Digital halftoning is a strategy to convert the color or gray scale image into a printable format. Among several halftoning techniques, error diffusion is one of the conventional and widely adopted method in many printing devices. In further, halftone classification is very important to obtain the perfect reconstruction of binary printed images. The paper attempts to solve this issue by exploiting the intrinsic similarity between the stochastic geometry and halftoning. Feature vectors are constructed using the point process statistic parameters such as directional distribution function and radially averaged power spectral density. Extreme learning machine model is developed and eight varieties of error diffusion halftone images are considered for classification. From the results, it has been validated that the proposed scheme yields better accuracy of 97.5% and it is faster than the existing approaches.**

I. INTRODUCTION

Halftone classification is one of the critical requisite for the perfect reconstruction of printed multimedia images. The prominent halftone techniques are ordered dithering (OD), error diffusion (ED), dot diffusion (DD) and iterative approach [1], [2]. Ordered dithering is the foremost approach and involves thresholding in a block-wise manner using a clustered- and dispersed-dot filters. In further, error and dot diffusion method are developed integrating diffusion filters and class matrix to obtain improved dot patterns. Finally, iterative approaches gained attention for its superior quality and texture, but the method is computational intensive and difficult to implement in hardware. Among many halftone methods, error diffusion [3] is predominantly adopted in many newspaper- and laser-printers. As shown in figure 1, the error diffusion [4] involves thresholding the input image through a constant threshold value and in further, diffusion kernel is applied which distributes the error to the neighborhood pixels through a specific weightage. Table 1, shows the eight different error diffusion techniques considered under this paper.

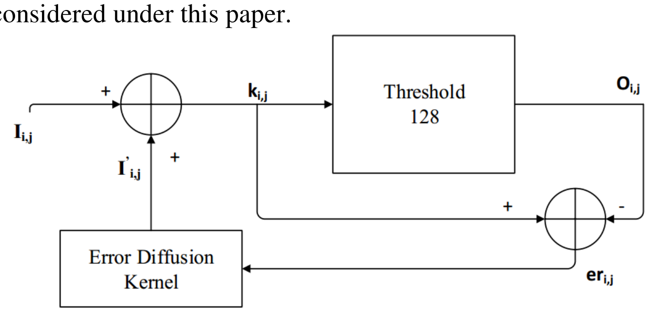

Fig. 1. Error diffusion technique

TABLE I: ERROR DIFFUSION TECHNIQUES

S. No	Error Diffusion Types	Abbreviation
1	Floyd- Steinberg	FED
2	Stucki	STED
3	Jarvis	JED
4	Burkes	BED
5	Atkinson	AED
6	Frankie Sierra	FSED
7	Filter Lite	FLED
8	Shaio Fan	SFED

And on many occasions, the restoration of the printed binary images is required for digital publishing, image compression and printed image processing. This is a difficult problem as various error diffusion kernels exist a very close dispersed dot pattern. The foremost approach on halftone classification is attempted by Chang. et. al [5], based on 1-D correlation analysis and three-layer back propagation neural network, and is limited to only five. Liu, et. al [6] proposed an another strategy based on least mean square filter to construct a feature and adopted naïve bayer classifier. Wen. et. al. [7] developed a statistical matrix descriptors based on the error diffusion kernels and classified six type of error diffused halftones. Zeng. et. al [8] used spectral regression kernel to build the feature vector and nearest centroid classifier to identify six error diffused halftone images. Finally, Zheng. et. al [9] adopted a deep learning neural network based on sparse auto-encoder to train and classify using majority voting strategy. The classification approach used in [5], [6], [7] and [8] mainly relies on the general statistical parameters like mean, variance and entropy to identify effective patches for training. But halftone images possess more complex patterns and cannot be perfectly characterized by the conventional statistical parameter. Though method [9] yields better result, it requires lot of training and computationally very intensive. In this paper, a new approach is attempted using the stochastic geometry parameters and extreme learning machine model is used to achieve the rapid estimation.

II. PROPOSED METHOD

Stochastic geometry deals with mathematical modelling and analysis of random geometrical patterns. For example, point process statistics under this theory deals with characterizing the distribution of points in space. This can be closely associated to halftone patterns, which comprise of randomly distributed binary values. At first, Ulichney [2] tried this mathematical approach to analyze the homogeneity and isotropic nature of the dispersed patterns. Two stochastic parameters such as directional distribution function (DDF) and radially average power spectral density (RAPSD) are formulated by partitioning the spatial and spectral domain as shown in figure 2. DDF is the measure of expected minority pixel per unit area and it provides the association of points in a segment to its neighborhood.

$$DDF_a(r1, r2) = \frac{E\{\Gamma_m^a | y \in \Phi\}/N(\Gamma_m^a)}{E\{\Gamma_m | y \in \Phi\}/N(\Gamma_m)} \qquad (1)$$

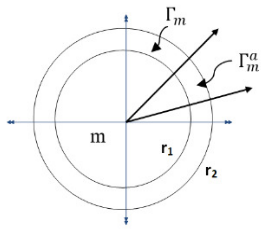

Fig. 2. Partitioned spatial domain

where $r1$ and $r2$ refers to the inner and outer radius of the segmented portion (Γ_m^a). And RAPSD is estimated by sectioning the frequency domain as provided in Eq. (2). $\hat{P}(f)$ and $N(R(f_p))$ refers to the spectral power and number of frequency samples.

$$RAPSD(f_\rho) = \frac{1}{N(R(f_p))} \sum_{f \epsilon R(f_p)} \hat{P}(f) \tag{2}$$

The feature vector is constructed combining the mentioned two parameters and it is found to be an effective indicator of pattern homogeneity.

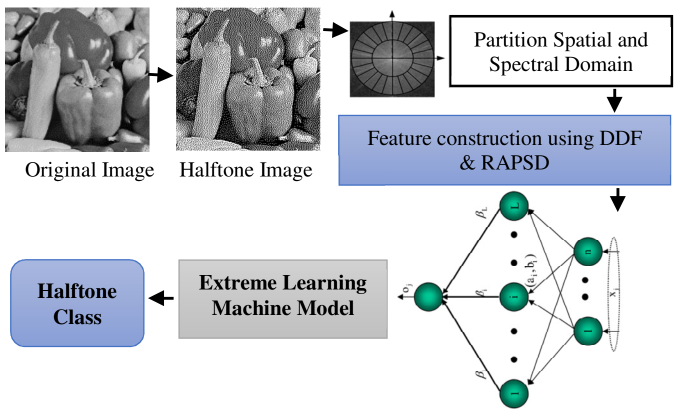

Fig 3. Proposed classification strategy

Fig. 4. Eight types of error diffusion

Figure 3 illustrates the proposed classification methodology, which begins with coverting the gray scale image into halftone version. Then the spatial and frequency domain is partitioned and statistical parameters are computed. Extreme learning machine (ELM) [10] is a basically a single hidden layer feed forward neural network which features kernel learning and random hidden nodes. ELM is known for its good generalization performance for multi classification problems and can learn very faster than the deep learning and machine learning kernels.

III. RESULTS

For performance evaluation, a halftone database (as shown in figure 4) is developed comprising of 100 images for each error diffusion class. ELM model is very simple to fine tune and optimal accuracy is obtained for number of hidden neurons of 1000 and radial basis function kernel. The average correct classification rate is used to evaluate the classification accuracy (ACCR).

TABLE II: ACCR FOR DIFFERENT SCHEMES

S. No	Ref.	Types	ACCR
1	[6]	3	98%
2	[7]	6	94%
3	[8], [9]	6	97%
4	Proposed	**8**	97.5%

From Table II, it can be inferred that the proposed technique has high classification accuracy (under more number of error diffusion types), it is important to mention that the proposed strategy is 10x times faster than other approaches [7], [8] and can be extended to other halftone types.

IV. CONCLUSION

A rapid and accurate halftone classification method for error diffused halftones is proposed in this paper. The technique utilizes inherent similarity between the stochastic statistical parameters and halftone patterns. Further, ELM is adopted to offer a simplistic yet powerful multiclass classifier model. From results, it can be inferred that the proposed scheme has high ACCR rate and in further can be generalized to other halftone types.

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