A Method for Classifying Halftone Patterns Based on Pattern Morphology

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Abstract

Different classification methods have been used to categorize the digital halftone algorithms and to help match the algorithms to the printer capabilities. The existing classification methods use the dot distribution, the dot generation process or a general description of the halftone pattern power spectra as basis for classification. Recent progress in understanding the interaction between the binary halftone patterns and the printer capabilities suggests that an optimal classification method may be based on the halftone pattern morphology. In this study, we review the existing classification methods, and introduce an alternative method based on the morphological similarities of binary halftone patterns. The method uses topological measurements of the halftone pattern to describe its morphology. The simplicity of the method permits its application to various areas of printing research such as printer characterization, toner deposition studies and development of printer models. As an example, we present a case study where we compared our proposed classification method with a commonly used method in their application to the development of a printer model. In this comparison our morphologically based classification method yielded improved printer predictions.

Introduction

After years of advancement, numerous halftone algorithms with diverse techniques have been invented and today halftone algorithm development continues to be an active research area [1, 2]. Concurrent with the development of the halftone algorithm techniques, various ad hoc classification methods came into use to fulfill the need of predicting the print quality of a given halftone algorithm and printer combination. There are many classification methods that evolved informally from the perspective of different authors, inevitably resulting in overlapping classifications. Our literature review identified three primary viewpoints under which the current classification methods may be grouped. These viewpoints are; classifications based on the halftone dot distribution, on the halftone dot generation technique and on the halftone dots power spectrum appearance.

From the viewpoint of the halftone dot distribution there is one main method with two principal categories, clustered dot and dispersed dot [3, 4] Clustered-dot algorithms turn on adjacent pixels to form a growing dot, while dispersed-dot turns pixels on individually without grouping them into a larger dot. The terms amplitude modulation (AM) and frequency modulation (FM) are often used instead of clustered or dispersed-dot [5]. Each of these categories can be subdivided according to whether the halftone dots are placed in a periodic (ordered) or an aperiodic (irregular) pattern [6, 7]. Occasionally, halftone algorithms are classified as hybrid dot [8] or micro clustered [9]. These are other names that correspond to the aperiodic-cluster-dot category.

From the viewpoint of the halftone dot generation technique we identify two main methods. The first method has two principal categories, adaptive or non-adaptive [10]. Adaptive refers to halftone algorithms that do direct calculations on the input image. The adaptive category is further subdivided into two subcategories, iterative and non-iterative. The adaptive-iterative algorithms are those that carry out more than one path of calculations on the continuous tone image while the adaptive non-iterative completes only one path. The non-adaptive category refers to algorithms that use a designed halftone screen [11]. The second commonly used method classifies the halftone algorithms into three main categories, point processes, neighborhood processes and iterative processes [12]. The point process category refers to halftone algorithms for which each pixel of the halftone image is a function of only one pixel of the continuous tone image. In the neighborhood process category, each pixel of the halftone image is a function of a local neighborhood of the continuous tone image. In the iterative process category the final halftone image is attained after several passes through the continuous tone image.

The final viewpoint is classification according to the halftone dots power spectrum appearance. The main classification method has two principal categories; blue and green noise. The blue noise category correspond to algorithms who's power spectrum has minimal low frequency components. Ulichney recognized blue noise as a desirable spectral property of visually pleasant halftone patterns [13]. The green noise category corresponds to algorithms who's power spectrum is composed mainly of mid range frequencies. Lau [14] recognized green noise as a desirable characteristic of halftoning techniques that resist the effects of printer distortions.

In practice, the current halftone algorithm classification methods have limited utility because they only provide a vague idea of the printed output quality. Recent progress in halftone research advocates that the characterization of the texture of the halftone pattern is important for the quantitative assessment of halftone quality [15, 16, 17]. Ultimately, the quality of the print depends on the interaction between the morphology of the halftone dots and the non-ideal behavior of the printer [18]. Printing research in the areas of printer characterization, toner deposition studies and development of printer models often require testing sets of halftone patterns with an assortment of morphologies. The use of a new classification criteria based on halftone pattern morphology would be useful for future progress in these areas.

In the following section we describe a halftone pattern classification method based on its morphology, followed by an evaluation and an example of its implementation.

Morphological Classification Method

Our approach to the morphological classification of halftone patterns consists of three steps; topology analysis, principal component analysis (PCA), and cluster analysis.

Topology Analysis

In this step, we extract the morphology information which is stored in the underlying pixel structure and the neighborhood relationship between the pixels of the halftone pattern. The morphology measurements are calculated through a topology analysis [19] of the halftone dots, consisting of defining the pixel neighborhood, identifying the connected components, and calculating the morphology measurements shown in Table 1.

We used a heuristic approach for selecting the morphology measurements. The first four morphology measurements on Table 1 (A_w, A, N_o, P) were selected because of their well documented effect on the average reflectance and the dot gain attributes of the printed image [14, 20]. The next two measurements (N_e, N_{me}) were selected because we found that they correlate well with the variance of the reflectance values of the printed image as illustrated in Figure 1. The following four measurements ($L_{maj}, L_{\min}, E, \theta_{maj}$) capture information about the size, symmetry and spatial orientation of the halftone dots. We used a known pattern recognition technique [21] to fit an ellipse to the halftone dots. The final measurement (N_v) is calculated from a voronoi tessellation of the halftone pattern and is an indirect measurement of the anisotropy of the pattern. The morphology information of each halftone pattern is arranged in a column vector $\vec{\mathbf{x}}$ and collected in the feature matrix $\mathbf{X}$ as shown in Equation 1.

$$\mathbf{X} = \left[\vec{\mathbf{x}}_{\mathbf{1}} \quad \cdots \quad \vec{\mathbf{x}}_{\mathbf{n}}\right] \tag{1}$$

Table 1 Morphological measurements used

Symbol	Description [22]
A_w	total area of dots weighted for different patterns of pixels within a 2x2 neighborhood
A	average dot area
N_o	total number of dots
P	total perimeter of dots
N_e	Euler number= total number of dots - the total number of holes
N_{me}	mean Euler number of dots
L_{maj}	length of ellipse major axis
$L_{\min}$	length of ellipse minor axis
E	Eccentricity the ratio of the distance between the foci of the ellipse and L_{maj}
θ_{maj}	angle between the x-axis and L_{maj}
N_v	number of Voronoi vertices

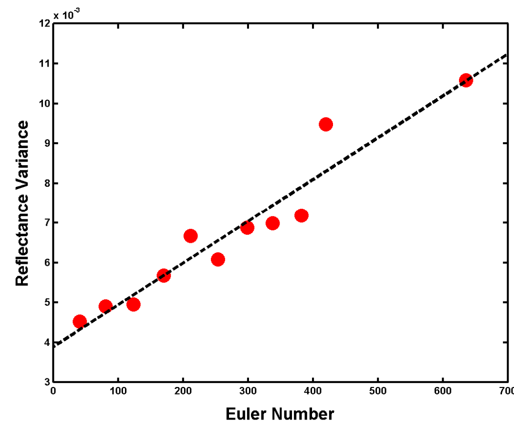

Figure 1: Euler Number vs. the variance of the reflectance values of the printed image for an error diffusion algorithm.

Principal Component Analysis (PCA)

The goal of the PCA [22] step is to eliminate any correlation that might exist between the morphological measurements of the feature matrix $\mathbf{X}$. The data is transformed to the principal component basis by matrix multiplication (Equation 2) with the projection matrix $\mathbf{P}$ who's rows are the principal components of $\mathbf{X}$. Halftone patterns that have similar morphologies will be close in distance within the principal component space.

$$\mathbf{Y} = \mathbf{PX} \tag{2}$$

Cluster Analysis

The goal of the cluster analysis is to group each halftone pattern into a cluster with other halftone patterns of similar morphology. We chose a hierarchical clustering technique [23] because it restricts each halftone pattern to belong to only one class, and the final classes can be adjusted without recalculation. The outcome of the hierarchical clustering technique is a cluster tree that shows the relationship among the different halftone patterns. The cluster tree is built by calculating the distance between each pair of halftone patterns and then linking the halftone patterns that are closer together to form the clusters, as clusters are created, clusters at one level are grouped into larger clusters at the next level until a complete tree is formed. If the cluster tree represents the data well there will be a strong linear correlation between the cluster distances (cophenetic distance) and the original distances between the halftone patterns. This correlation is measured by the cophenetic correlation coefficient.

Choosing a threshold value for the cophenetic distance defines the number of clusters. Although various techniques have been reported to assist in the selection of the threshold [24], this value should be selected by inspection of various cluster combinations given that the definition of a “good” morphological cluster is completely subjective.

Testing the Method

The classification method was tested with 132 binary halftone patterns from seven halftone algorithms representing a wide range of halftone morphologies. The hierarchical clustering was evaluated with various combinations of distance metrics and linkage methods [22]. Results shown on Table 2 illustrate that the highest cophenetic correlation coefficient is obtained with the combination of the Euclidian metric and the centroid linkage method. This combination was chosen to build the hierarchical tree shown in the dendogram in Figure 2. In the dendogram, the x axis represents the halftone patterns with a cluster number and the y axis represents the cophenetic distance. The inverted U-shape lines demonstrate the links between the clusters.

Table 2 Cophenetic correlation coefficient for various combinations of distance metrics and linkage methods.

Distance / Link	Euclidian	Std. Euclidian	City Block	Mahalanobis
Nearest	0.867	0.518	0.800	0.518
Farthest	0.885	0.482	0.818	0.482
Average	0.896	0.510	0.836	0.510
Centroid	0.903	0.534		
Ward	0.852	0.410		

The cophenetic distance threshold was selected by visual inspection of the halftone patterns. A group of observers evaluated the clusters at various thresholds and determined that a threshold value of 0.80 partitioned the data into 18 visually similar clusters. Figure 3 shows examples of two representative clusters obtained during testing.

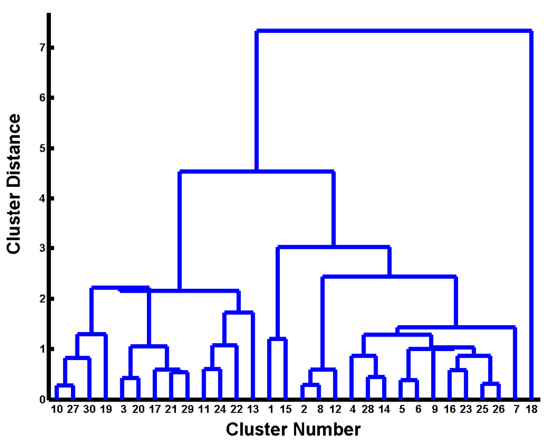

Figure 2: Dendrogram showing the top 30 clusters when characterized with the Euclidian distance metric and the centroid linkage method.

Case Study: Application to printer modeling

We developed an electrophotographic printer model on the premise that the printer is a texture transformation machine. The model consists of a feed-forward neural network (Figure 4) designed to map a parametric representation of the input halftone pattern texture ($\vec{\mathbf{m}}$) into a parametric representation of the output texture ($\vec{\mathbf{n}}$). Our focus is to illustrate an application of the morphology classification method, therefore details about the construction and selection of the texture parameters and the neural network architecture will be described in a future publication. The morphology classification method and the classification method based on dot distribution were used to select a set of halftone patterns to train the neural network. Selecting a training set according to the dot distribution viewpoint was challenging due to the lack of clear criteria to distinguish between the halftone patterns. We had to rely on engineering judgment to choose halftone patterns from the clustered-dot, dispersed dot and hybrid categories. In contrast, the selection of a training set using the morphology classification method was fairly simple. The training set was built by randomly selecting a member from each of the 18 clusters obtained when using a classification threshold value of 0.80.

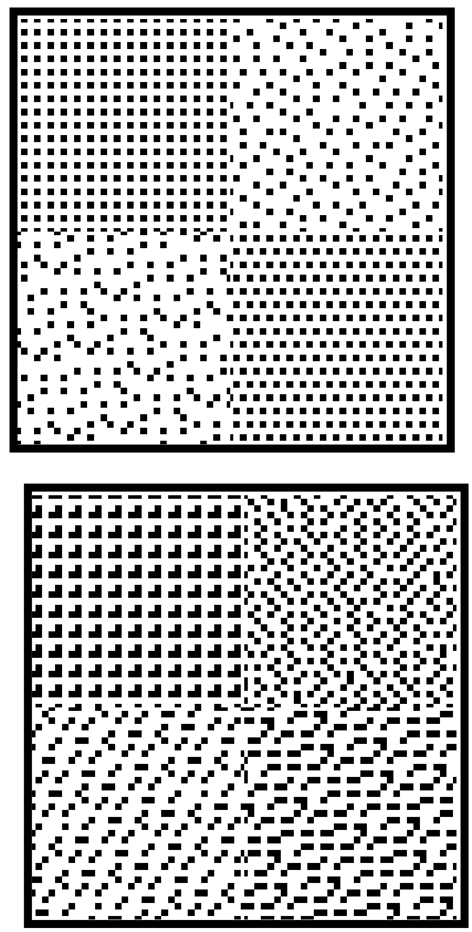

Figure 3: Two clusters obtained during testing. The top cluster groups patterns with non-connected, nearly equidistant pixels. The bottom cluster groups patterns with small L-shape components and a diagonal slant character.

$$\begin{bmatrix}\textbf{Halftone}\\ \textbf{Pattern}\end{bmatrix} \Rightarrow \overset{\vec{\mathbf{m}}}{\begin{bmatrix} m_1 \\ m_2 \\ \vdots \\ m_k \end{bmatrix}} \Rightarrow \begin{bmatrix}\textbf{Neural}\\ \textbf{Network}\end{bmatrix} \Rightarrow \overset{\vec{\mathbf{n}}}{\begin{bmatrix} n_1 \\ n_2 \\ \vdots \\ n_k \end{bmatrix}} \Rightarrow \begin{bmatrix}\textbf{Printed}\\ \textbf{Pattern}\end{bmatrix}$$

Figure 4: A neural network printer model that transforms the input texture pattern $\vec{\mathbf{m}}$ into the output texture pattern $\vec{\mathbf{n}}$.

The neural network model was trained separately with each of the training sets. Once trained, the model was used to predict the reflectance statistics for an independent set of halftone patterns. The performance of the model was evaluated by calculating the linear correlation coefficient between the modeled and the measured values for each reflectance statistic (mean, variance and skewness). Table 3 shows an example of the correlation coefficient values obtained when modeling a 4x4 pixel clustered dot pattern. Improved printer model predictions were obtained with the training set selected by the morphology classification method compared to the training set selected by the dot distribution method as supported by significantly higher correlation coefficient values.

Table 3: Modeled vs. Measured Correlation Coefficients for various reflectance statistics.

	Morphology Method	Dot Distribution Method
Mean	0.998	0.445
Variance	0.978	0.743
Skewness	0.904	0.638

Conclusions

We present a method for the classification of binary halftone patterns based on 11 morphological measurements. The method was used for the selection of a training set in a neural network printer model. Our results show that the training set selected by our alternative classification method yields improved printer model predictions compared to a training set selected by a classification method based on dot distribution. The method assures no overlap between classification groups and allows the user to easily adjust the final classes to match their specific application. The morphology classification method may find application in other areas of research such as; printer characterization and toner deposition studies.

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