DEGRADATION SPECIFIC OCR

by

Subramaniam Venkatraman

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Subramaniam Venkatraman

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Elisa Barney Smith, Ph.D.	Chair, Supervisory Committee
Thad Welch, Ph.D.	Member, Supervisory Committee
Tim Andersen, Ph.D.	Member, Supervisory Committee

The final reading approval of the thesis was granted by Elisa Barney Smith, Ph.D., Chair, Supervisory Committee. The thesis was approved for the Graduate College by John R. Pelton, Ph.D., Dean of the Graduate College.

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ABSTRACT

Optical Character Recognition (OCR) is the mechanical or electronic translation of scanned images of handwritten, typewritten, or printed text into machine-encoded text. OCR has many applications, such as enabling a text document in a physical form to be editable, or enabling computer searching on a computer of a text that was initially in printed form. OCR engines are widely used to digitize text documents so that they can be digitally stored for remote access, mainly for websites. This facilitates the availability of these invaluable resources instantly, no matter the geographical location of the end user. Huge OCR misclassification errors can occur when an OCR engine is used to digitize a document that is degraded. The degradation may be due to varied reasons, including aging of the paper, incomplete printed characters, and blots of ink on the original document. In this thesis, the degradation due to scanning text documents was considered. To improve the OCR performance, it is vital to train the classifier on a large training set that has significant data points similar to the degraded real-life characters. In this thesis, characters with varying degrees of blurring and binarization thresholds were generated and they were used to calculate Edge Spread degradation parameters. These parameters were then used to divide the training data set of the OCR engine into more homogeneous sets. The resulting classification accuracy by training on these smaller sets was analyzed.

The training data set consisted of 100,000 data points of 300 DPI, 12 point Sans Serif font lowercase characters ‘c and ‘e’. These characters were generated with random values of threshold and blur width with random Gaussian noise added. To group the similar degraded characters together, clustering was performed using the Isodata clustering algo-

rithm. The two edge-spread parameters, one calculated on isolated edges named DC, one calculated on edges in close proximity accounting for interference effects, named MDC, were estimated to fit the cluster boundaries. These values were then used to divide the training data and a Bayesian classifier was used for recognition. It was verified that MDC is slightly better than DC as a division parameter. A choice of either 2 or 3 partitions was found to be the best choice for dataset division. An experimental way to estimate the best boundary to divide the data set was determined and tests were conducted that verified it.

Both crisp and fuzzy approaches for classifier training and testing were implemented and various combinations were tried with the crisp training and fuzzy testing being the best approach, giving a 98.08% classification rate for the data set divided into 2 partitions and 98.93% classification rate for the data set divided into 3 partitions in comparison to 94.08% for the classification of the data set with no divisions.

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CHAPTER 1

INTRODUCTION

The world is rapidly moving towards the extensive use of computers and digital media to access information. An increasing number of people are using the internet as the most trusted source to get information, search for articles, read the news and update themselves with all other day to day scholarly as well as routine chores. This transition to digital media has been made possible by the advancement in internet technology which has kept pace with this exponential demand and thus we can depend on technology to get information from remote locations instantaneously. This demand in digital copies has resulted in an increased demand for journals, articles and other literature to be available in a digitized version. It is especially useful to have articles that have a limited circulation or availability, such as old books which are no longer in publication, rare manuscripts and research articles, available digitally. If we can stay clear of any copyright violation, the digital availability of these invaluable resources, coupled with the fact that they can be accessed instantly through the web is invaluable in research and also helps to keep record of previous work. In order to digitize, it is impractical to get a person to type all these articles, books and other invaluable literature. This necessitates the use of Optical Character Recognition (OCR) to implement this conversion from images of text to digital text documents. The OCR engines convert the undegraded documents into corresponding digital copies with an acceptable accuracy rate, which is saved and can be made available online.

The documents that are scanned and subsequently converted to digital copies by OCR engines may be degraded due to various reasons, thus affecting the performance of the OCR engine. The reasons include improper printing of the original document, aging of the original book or journal, etc. The degradation effects due to the previously mentioned reasons are not modeled in this thesis. Degradations introduced due to scanning text documents are considered in this thesis.

In this thesis, the dataset considered is comprised of characters ‘c’ and ‘e’ because they pose the biggest challenge for modern day classifiers due to similarities in appearance. If the classifier performance is good with worst case data, it should perform better on any other data set. The character appearance variations of printed characters ‘c’ and ‘e’ caused by scanning degradation with different stroke widths is shown in Figure 1.1. The difference between the ideal and the degraded character is significant, as seen in the figure. Figure 1.1 shows the ideal printed characters, characters with a thin stroke thickness as well as characters with thick stroke widths. These variations seen in the character appearance are due to degradations discussed in detail in the following paragraphs.

We have to make sure that the classifier in the OCR engine is trained on all of the variations of the characters shown, as these patterns are encountered frequently by OCR engines in their daily operations. It can be visually concluded that if the OCR engine is trained to only identify the ideal characters, the non-ideal characters, which are a slight variation of the ideal characters shown in Figure 1.1, may be misclassified due to insufficient training. This will lead to a sizeable classification error in the final transcript and hence has to be handled in training to reduce the error.

The scanning degradations can be described in the context of the degradation model

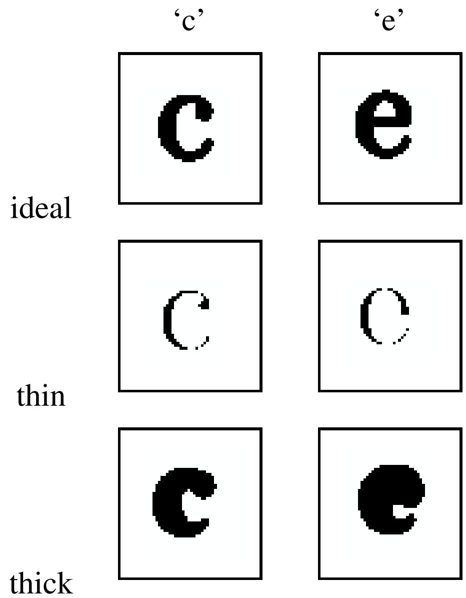


Figure 1.1: Ideal, thin and thick characters ‘c’ and ‘e’.

by Baird [10]. When a printed line is scanned, there are two possibilities: thickening or thinning of the original line. This is referred to as a degradation because the scanned image is not exactly the same as the original scanned image. Analysis is required to determine by how much the degradation introduced has thickened or thinned the scanned lines. The major factors that cause degradation in an image passed through a scanner are the point spread function (PSF), which causes the blur, and the binarization threshold. The point spread function describes the effect of reflection of light from the different optics of the scanner when an image is scanned.

It is relatively common to design classifiers under the assumption that there is large within class similarity and low between class similarity in the training dataset. The within class similarity is often increased by restricting the problem to a “common” domain, or dividing a larger non-homogeneous problem into multiple problems, each of which exhibit larger homogeneity. This has often been done in OCR problems by assuming a common font in a machine printed text or a single writer in a handwritten text. The approach of using a particular font and style requires that some form of font/style detection be employed in order to select the appropriate classifier (the one that was trained on the font style being recognized) during execution. To improve classifier performance when the input is not guaranteed to be homogeneous, it is also desirable to have a large and varied training set to improve the ability of the classifier to generalize. This, however, leads to lower within class similarity.

Other approaches have been explored to partition the dataset to improve OCR results. These vary in the classifier used, training data used, training method employed, and a host of other factors. The basic idea explored in all the research papers related to this topic is grouping the training data into isogenous patterns. Xiu et al. [1] talk about a style-based approach to improve overall accuracy of paper ballot mark recognition to get a valid count of votes cast in an election. The method used to determine the style did not evaluate every mark on the ballot in isolation, but the decision was made after analyzing all the marks made on a particular ballot form by a voter. Thus, the consistency of marks of the voter across the ballot and the inherent style was used to judge and decide a valid vote. Xiu and Baird [2] exploited the strong visual consistency of font and degradation within a book, which is generally an isogenous pattern due to the same font size and font style seen on a page of text, to conclude the style. The style information was then used as a parameter to train the classifier and greater accuracy was achieved in the classification of text in books.

Another idea to get more homogeneity within the training dataset is dividing by font type. Baird and Nagy [3] suggested a way to improve the classification accuracy of a polyfont classifier that is capable of recognizing any of 100 typefaces moderately well. The method suggested is to specially train the classifier in the OCR engine on the single font it is currently analyzing. The decision on the current font and size is arrived at after analyzing a few images and determining the font. This training on a particular font requires manual intervention in this otherwise automatic process. Sarkar and Nagy [4, 5, 6] observed that in many applications of pattern recognition, patterns appear in groups and have a common origin. An example would be a printed word with characters that comprise that word in the same font. The common origin leaves its style imprint on its patterns, resulting in style consistency. Tests were done on handwritten as well as printed text using a style specific classifier to prove that modeling style dependencies among constituent patterns of a field improved classification accuracy. This is possible because data used in OCR engines have different styles that are distinct, and hence this feature has been exploited.

Many approaches have been followed to partition the dataset into smaller homogeneous partitions to improve the classifier performance. The approach to implement within class similarity proposed in this thesis is grouping the data by degradation parameters that are introduced during scanning. This grouping of degraded characters is done based on their visual appearance (i.e., thick/thin/medium) of the character strokes. The changes in stroke widths due to scanning have been modeled and a mathematical formula has been developed to describe them [8, 9]. The model to estimate the stroke thickness uses the blur width w and binarization threshold θ, which in turn relate to edge spread degradation parameters. Dividing the dataset by the character being thick or thin is one way of partitioning, but there are numerous other ways that have been explored. Barney Smith and Andersen [7] analyzed and experimented on how the classifier accuracy of an OCR engine can be improved by training with a dataset that resembles more closely the degraded character to which the OCR engine is subjected. They discovered that, while dividing the dataset by width w or threshold θ individually improves the performance over classification of an unpartitioned dataset, the edge spread degradation parameter was a better partitioning parameter compared to others. In spite of all this analysis, there is still room for improvement and we can come up with better partitioning parameters to divide the dataset. More analysis needs to be done to come up with answers on how many regions to divide the dataset into, at what value, what parameter to use, and whether an edge spread model based on isolated edges or one that considers adjacent edge interference is better.

The tests implemented in this thesis were motivated by the goal to explore and answer the following six questions. These questions are:

1. Did the division of the dataset improve the accuracy of classifying the dataset?

2. Is an edge spread that considers adjacent edge scanning interference a better parameter to partition the dataset than an edge spread parameter based on scanning isolated edges?

3. If the dataset was divided by the incorrect values, how does it affect the performance?

4. What is the reasonable number of partitions into which a dataset should be divided?

5. What is the error associated with estimating the wrong edge spread degradation parameters for a character?

6. Does the use of a fuzzy approach of classification offer any improvement in performance over the crisp approach?

To analyze the ideas suggested in this thesis, many components and algorithms were implemented. Chapter 2 gives technical background related to the division of the dataspace using edge spread parameters. This chapter includes details of the degradation model that is used to generate the degraded training set. The edge spread degradation parameters are introduced and mathematical formulae to estimate them are discussed. This chapter also describes briefly the Bayesian classifier and the Isodata clustering algorithm used to classify and cluster OCR training data. A brief background of the different classifier approaches that have been implemented to improve the performance is presented. Chapter 3 gives details of the experiments done to evaluate how the new edge spread parameter that considers adjacent edge scanning interference is better than the edge spread parameter based on scanning of isolated edges. Chapter 4 talks about the analysis and conclusions that we can arrive at after seeing the results and also a few ideas on further improving the scope of this idea to get better OCR classification results.

CHAPTER 2

TECHNICAL BACKGROUND

The dataset used in this thesis is comprised of the degraded characters ‘c’ and ‘e’. These two characters were selected because of their high visual similarity. These characters pose the greatest challenge for classifiers to classify and thus are extensively used to evaluate classifiers. It is very difficult to generate a representative training dataset from scanned documents. If a training dataset is not a representative dataset, it generally results in a poorly trained classifier. A scanner model was used to generate synthetic degraded ‘c’ and ‘e’ character samples with varying stroke widths. We generated synthetic characters instead of real scanned characters because even though we encounter a large variation in real documents with different stroke widths, calculating the degradation parameters after these documents are scanned is difficult. This is mainly due to the cost associated with calibrating real documents, which is time consuming, and thus increases the cost of that operation. A better, cost effective approach is to synthetically generate characters in the training dataset with known parameters so that the scanned degradation can be easily estimated from them. Subsection 2.1.1 will discuss the degradation model used to generate the degraded characters used to train and evaluate the classifier. Degradation parameters are calculated from the characters that will then be used to divide the training dataset. In this thesis, the degradation parameters that are being considered are edge spread degradation measures. The subsequent Section 2.1.2 describes the edge spread degradation parameter, which is applicable to edges in isolation and is a combination of w and θ called DC. It was initially used to partition the degradation space by Barney Smith and Andersen [7] and proved to be a better division parameter than using either undivided data, division by PSF width or binarization threshold alone. McGillivary [9] developed a formulation for the edge spread when two edges are close enough to interfere called MDC. This parameter is a better description of the stroke width changes when lines or strokes frequently seen in real-life text are scanned. Section 2.1.3 elaborates on the background and evaluation of the edge spread parameter MDC.

In this thesis, the DC and MDC values are used to divide the data into homogeneous datasets. Clustering is an unsupervised algorithm that groups characters that have similar features. The number of resultant clusters is chosen by the user. The fundamental assumption made in clustering and the subsequent DC and MDC boundary fitting is that elements belonging to the same cluster partion have similar appearance. This in turn leads to similar features for these visually similar characters. The Isodata clustering algorithm will group these similar characters together. Section 2.2 elaborates on the details of this algorithm.

After the training data has been clustered using the Isodata algorithm, the DC and MDC values that best fit the boundary between the clusters are estimated. This value is then used to divide the training data set of the classifier. The choice of classifier is made keeping in mind the ease of training and classification accuracy, among other factors. Subsection 2.3.1 talks about the Bayesian classifier that is used to classify the dataset partitioned by DC and MDC.

The Bayesian classifier used to classify the partitioned dataset belongs to the class of crisp decision boundary classifiers. This may result in misclassification due to the inability to decide perfectly to which partition an unclassified degraded datapoint should be assigned and because the boundaries are between gradually varying images, not distinctly grouped ones. This can be improved by implementing a decision boundary where the values are weighted by values on either side of the partition and then making a decision to assign a unclassified test point. This approach is motivated by fuzzy logic. In this logic, we do not associate crisp decisions in point membership, which in our case is saying a test point belongs definitely to a certain partition and not in the other. We rather consider the probabilities of the test point being in either partition and we account for this when calculations are done on that test point. Subsections 2.3.2 through 2.3.5 talk about the various classification approaches that have been implemented to improve the performance over the crisp Bayesian classifier.

2.1 Generating Synthetic Scanned Images

The degradation model used in this thesis is based on the model proposed by Baird [10]. The degradation model describes the acquisition of a binary scanned image as a multistage process. The process begins with an ideal spatially continuous bilevel image that is convolved and then sampled by a point spread function (PSF). Next Gaussian noise is added to this sampled image to simulate the noise introduced during actual scanning and also to account for noise that would have been originally present on the paper image before it was scanned. Finally, the image is binarized at a certain threshold level to produce the binary scanned image. This flow of operations is shown in Figure 2.1.

The section begins with a detailed mathematical description of the scanner model that is used to generate the degraded characters. We then move on to explain the mathematical description and calculation of the degradation parameters DC and MDC. After the calculation of the edge spread degradation parameters, the following section talks about the idea of dividing the OCR training dataset partitioned by the edge degradation parameters DC and MDC.

2.1.1 Basic Scanner Model

The basic scanner model is used to synthetically generate characters with varying values of PSF width and threshold values, which are used to calculate the edge spread degradation parameters. These parameters are used to binarize the grey level image to simulate the scanning degradation synthetically. There are other degradations that could affect a character but they are not accounted for by this model. This model takes a spatially continuous bilevel image and converts it to a spatially discrete bilevel image and tries to replicate the errors and discrepancies that are introduced due to the actual scanning of a text document. The image that is under consideration in this model is made of "blackness" or absorptance, *o(x,y)*. Absorptance can be expressed as one minus the reflectance. The possible values of the original image *o(x,y)* are 0 (white) or 1 (black). This input image is digitized by a sensor array in the scanner assembly. The digitization operation of the image can be modeled by using a Point Spread Function (PSF), which is the 2-D impulse response of a scanner. The shape variance of the PSF accounts for the fact that for each point on a physical paper image that is scanned, different amounts of light are reflected to each sensor at the detection end by the different components of an image. The existence of equivalence means that this convolution can be used to predict the amount of reflected light each sensor detects. If the image is sampled at points x_j, y_i on a rectangular grid, then the resultant sampled image *s[i,j]* is given by the expression

$$s[i,j] = \int\int PSF(x_j - u, y_i - v) \cdot o(u,v) du dv. \tag{2.1}$$

The assumption made in Equation 2.1 is that the scanner is spatially invariant over the field of view, which is valid more so for small regions.

In order to account for and replicate the noise that would exist on the original image and the noise that is introduced during scanning, Gaussian noise *n[i,j]* is added to the image,

$$a[i,j] = s[i,j] + n[i,j]. \tag{2.2}$$

Gaussian noise is added to every sensor independently. This additive noise has a mean of zero and a standard deviation of σ_{noise}.

The resulting intensity is quantized using a thresholding operation

$$f[i,j] = \begin{cases} 1 & a[i,j] \geq \theta \\ 0 & a[i,j] < \theta \end{cases}. \tag{2.3}$$

A higher threshold value of θ, reduces the number of black pixels that comprise the foreground in the resultant image *f[i,j]*. This whole process is combined in the diagram shown in Figure 2.1.

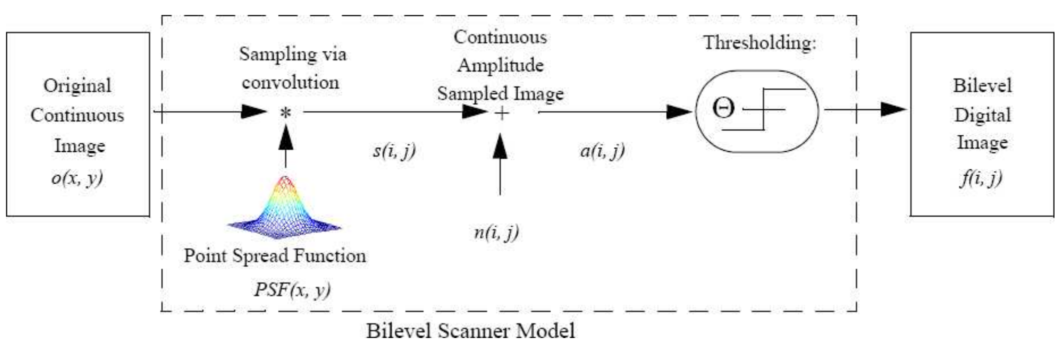


Figure 2.1: This scanner model is used to determine the value of the pixel *f[i,j]* centered on each sensor element[10].

The PSF shape selected in the scanner model must satisfy two properties. The first requirement is that the total volume under the PSF selected must be 1. The second requirement is that the PSF function must be non-negative everywhere.

In addition to these two requirements, there are three assumptions that are made about the PSF that are helpful for the analysis in this thesis. The first assumption made is that the PSF should be circularly symmetric about the origin. This is necessary because, unless this assumption is made, objects with different orientations would be affected differently by the PSF. The second assumption made is that the PSF should decrease monotonically as we start moving from the origin towards the image boundary. This assumption is made in order to prevent an introduction of unintended ripples in the image intensity that are not present in actual document images. These effects would complicate our analysis. The final assumption made is that the shape of the PSF should be described in terms of a single parameter w, which describes the width of the PSF.

Many PSF shapes satisfy these requirements. In this thesis, a bivariate Gaussian is used for the PSF. This PSF shape is used primarily because of its familiarity to researchers and because it is easy to accurately simulate the convolution. The equation for the bivariate Gaussian is

$$PSF_{Gaussian}(x,y;w) = \frac{1}{2\pi w^2} \exp\left(\frac{-(x^2+y^2)}{2w^2}\right). \tag{2.4}$$

In the equation, the value of w is measured in units of pixels.

2.1.2 Edge Spread, Delta_C (DC)

When isolated straight edges in images are scanned using the basic scanner model described previously, they get degraded in several ways. After convolving the scanned edge with the PSF, the intensity of pixels as a function of their distance from the original edge is defined by their edge spread function (ESF). Figure 2.2 shows the ESFs that result from Gaussian PSFs with two different values of w. The cumulative marginal of the PSF gives the ESF

$$ESF(x;w) = \int_{-\infty}^{x} \int_{-\infty}^{\infty} PSF(\hat{x}, y; w) dy d\hat{x}. \tag{2.5}$$

It can be shown that the ESF for a Gaussian distribution is

$$ESF_{Gauss}(x;w) = ESF_{Gauss}\left(\frac{x}{w}\right) = \frac{1}{2} \cdot erf\left(\frac{x}{w \cdot \sqrt{2}}\right) + \frac{1}{2}, \tag{2.6}$$

where erf is given by

$$erf(x) = \frac{2}{\sqrt{\pi}} \int_{0}^{x} e^{-t^2} dt. \tag{2.7}$$

When the image of a scanned edge is binarized, its position changes from its original location. This change in the scanned position is shown in Figure 2.2. The new edge location occurs where the amplitude equals the threshold θ,

$$ESF\left(\frac{x}{w}\right) = \theta. \tag{2.8}$$

The new position would occur at x = -DC, where

$$DC = -w \cdot ESF^{-1}(\theta). \tag{2.9}$$

It can be inferred from Equation 2.9 that there are multiple values of w and θ that will result in the same value of DC and, therefore, produce the same distortion on an isolated edge [11]. Figure 2.3 shows an multiple DC isocline plots for different DC values. The x-axis is the PSF width w and the y-axis is the binarization threshold θ. It can be seen from

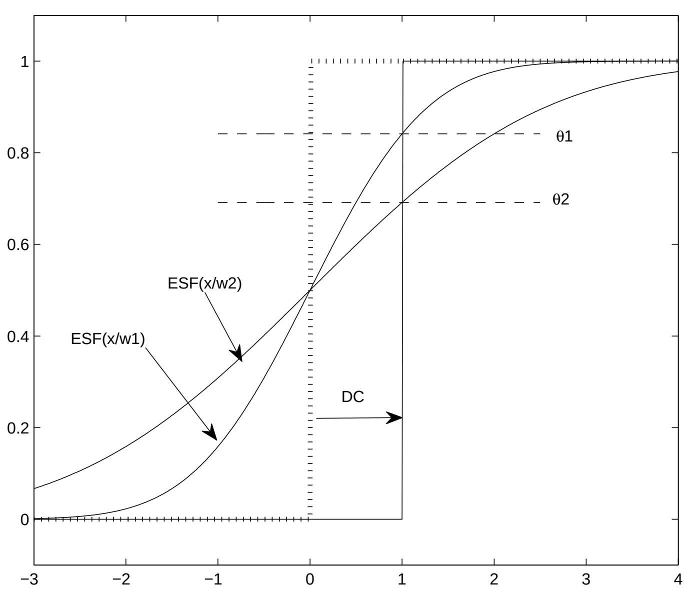


Figure 2.2: Gaussian ESFs are shown with w1=1 and w2=2. When the image is blurred and thresholded, the position of the edge is shifted from the dotted step function to the solid step edge function. This shift is called DC and is by convention positive when the edge is shifted to the left [9].

the plot of the isocline DC lines that the DC lines extend over the entire range of w and θ values.

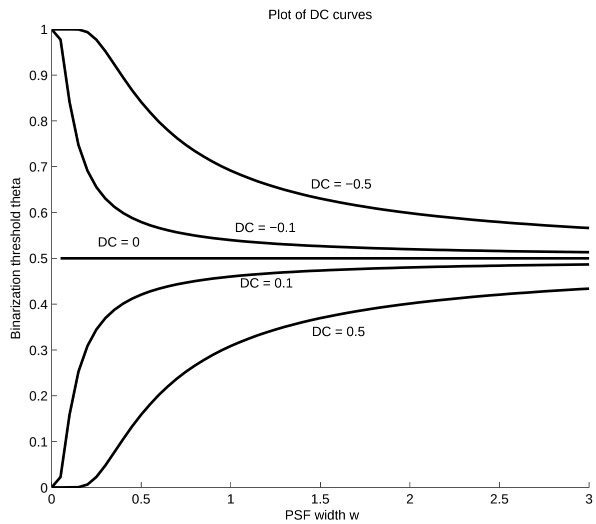


Figure 2.3: Edge spread degradation parameter DC isocline lines for DC values -0.1, -0.5, 0, 0.1 and 0.5.

2.1.3 Stroke Spread, Modified Delta_C (MDC)

In the previous subsection, we discussed the effect of scanning on isolated edges. In this section, we will discuss the effect of scanning on pairs of adjacent edges, also knows as strokes. Character images contain many edges like this. Scanning changes the thickness of these strokes. This change in thickness is not the same as the shift predicted for isolated edges because the opposite edges in the stroke interfere with one another. This effect was analyzed and formulated mathematically by McGillivary in his thesis [9]. If the edges are parallel, the one dimensional cross section of a scanned stroke is a square pulse with a width τ. Let us assume that the square pulse is centered at the origin. In this case, the value of pixels as a function of their position, $s(x)$, can be determined using

$$s(x) = s(-x) = ESF\left(\frac{\tau - 2x}{2w}\right) - ESF\left(\frac{-\tau - 2x}{2w}\right). \tag{2.10}$$

Similar to the scanned edges, the new edge locations occur where *s(x)* is equal to θ. Let us denote the thickness of the stroke after thresholding by $\tau_{scanned}$, and if it is found to be greater than zero, then the threshold is given by

$$\theta = ESF\left(\frac{\tau - \tau_{Scanned}}{2w}\right) - ESF\left(\frac{-\tau - \tau_{Scanned}}{2w}\right). \tag{2.11}$$

The change in stroke thickness MDC can be defined as

$$\tau_{scanned} = \tau + MDC, \tag{2.12}$$

which leads to

$$\theta = ESF\left(\frac{-MDC}{2w}\right) - ESF\left(\frac{-2\tau - MDC}{2w}\right). \tag{2.13}$$

As the τ value gets bigger, Equation 2.13 becomes

$$\theta = ESF\left(\frac{-MDC}{2w}\right). \tag{2.14}$$

When τ is large enough to make the edges independent, the change in stroke thickness becomes twice the DC.

In addition to the occurrence of change in stroke thickness, there is also a chance that a stroke will disappear altogether. This will occur at instances when the threshold exceeds the maximum value of *s(x)*. The value of threshold selected affects the image in the sense that a higher threshold value ensures fewer black pixels in the resulting image and vice versa. We can find this θ_{max} by setting $\tau_{scanned}$ in Equation 2.11 to zero, which results in

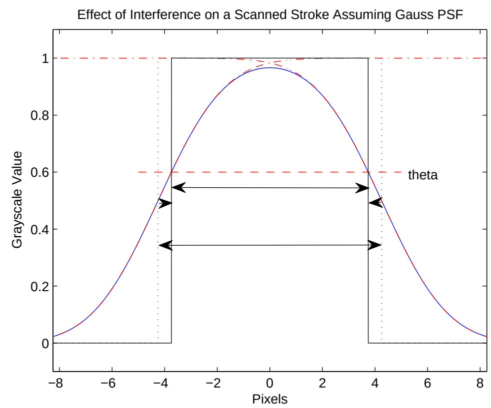


Figure 2.4: When a stroke characterized by two parallel edges is scanned, the resulting stroke thickness changes. Interference between the parallel edges causes the grayscale value of pixels to be less than that predicted by the ESF. As a result, the stroke thickness will be less than that predicted by DC.

$$\theta_{max} = ESF\left(\frac{\tau}{2w}\right) - ESF\left(-\frac{\tau}{2w}\right) = 1 - 2 \cdot ESF\left(-\frac{\tau}{2w}\right). \tag{2.15}$$

First it must be verified if θ is greater than θ_{max} by using Equation 2.15. If it is, the stroke vanishes. Once this is verified, the upper and lower bounds on values of MDC are set. These bounds are

$$MDC > -\tau, \tag{2.16}$$

and

$$MDC \leq 2 \cdot DC. \tag{2.17}$$

Thus, we can state that at larger τ values

$$DC = \frac{MDC}{2}. \tag{2.18}$$

The lower bound limits on the value of MDC comes from the fact that $\tau_{Scanned}$ cannot be negative and the upper bound comes from Equations 2.7 and 2.9, and the fact that the

ESF is always positive. For a given set of values for τ, w, and θ, it is possible to determine the value of MDC. The maximum and minimum bounds on the value of MDC value are calculated, and interpolation is done between the maximum and minimum values of MDC, indicated by Equations 2.16 and 2.17, respectively, to estimate the MDC value.

Similar to Figure 2.3, which depicts an isocline plot of many DC values plotted on the same graph, Figure 2.5 shows multiple MDC isoclines drawn simultaneously. The important aspect that is visible instantly is that the plots of DC and MDC lines do not match. The MDC curves slope down as PSF width increases in comparison to DC lines.

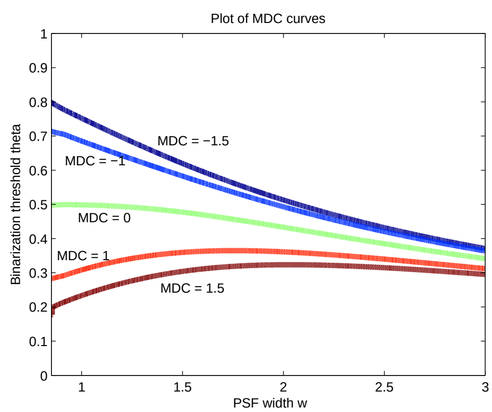


Figure 2.5: Edge spread degradation parameter MDC Isocline lines for MDC values -1.5, -1, 0, 1, and 1.5.

2.2 Clustering

Clustering is a method of classification that groups data with similar features. In pattern recognition, we try to find elements sharing a region in the feature space, because elements of a particular class will generally lie closer to each other. Since labeling each feature vector can be a costly operation, it is desirable to simply cluster similar feature vectors without the knowledge of their class. Once such clusters have been formed, it is easier to label the clusters and perform any error analysis. There are many clustering algorithms used in pattern classification. The following subsections talk about the Isodata or C-means clustering and Fuzzy C-means clustering algorithms used in this thesis.

2.2.1 Isodata Clustering

Isodata stands for Iterative self-organizing data analysis technique. This is also sometimes called C-Means. Isodata is the algorithm used to cluster the characters in this thesis. The first step is to decide into how many clusters, C, the data needs to be divided. This algorithm works by first randomly selecting C points from the dataset, depending on the desired number of clusters, as means. These will be the means used to group the data. After the mean values have been selected, data is grouped into clusters. To cluster the data, a 1 nearest neighbor method was used. Distances are compared from the C randomly selected means to find the points in the dataset closest to these point means in consideration and adding the closest points to the respective cluster to which these mean points belong. After every iteration, the cluster means are updated based on points associated with the means in the previous iteration. Then, all the points are again associated with the new means and this iterative approach continues until none of the cluster means change. The point at which none of the means change tells us that the datapoints have been grouped as close to the cluster center as possible.

2.2.2 Fuzzy C-Means Clustering

Fuzzy C-means (FCM) is a data clustering technique in which a dataset is grouped into C clusters with every datapoint in the dataset having membership in every cluster partition to a certain degree. The membership function $\mu(x)$ is the basic idea in fuzzy set theory;

its values measure degrees to which objects satisfy imprecisely defined properties, which in our case is the cluster assignment of a point. The membership of a point in a particular cluster partition is inversely proportional to the distance from the cluster partition. Consider the two examples that follow to understand this concept of membership. First consider a certain datapoint that lies close to the center of a cluster partition, it will have a higher degree of belonging or membership to that cluster partition than in other cluster partitions. Next consider another datapoint that lies far away from the center of a cluster partition; it will have a low degree of belonging or membership to that cluster partition and greater membership to a neighboring cluster partition it lies closer to.

The logic of this algorithm starts with first deciding on the final number of clusters, C, followed by an initial guess for the cluster partition centers, which are intended to mark the mean location of each resultant cluster partition. The initial guess for these cluster partition centers is most likely incorrect. The next step in the algorithm is to assign every datapoint a membership grade for each cluster partition randomly between 0 and 1, then compute the centroid for each cluster partition followed by computing the membership function for each point of being in the cluster partitions. The calculation of centroid and membership function is repeated until the algorithm has converged (i.e., the change in coefficients between successive iterations is not more than a small value referred to as the sensitivity threshold). By iteratively updating the cluster partition centers and the membership grades for each datapoint, this fuzzy C-means algorithm iteratively moves the cluster partition centers to the right location within a dataset. This iteration is based on minimizing an objective function that represents the distance from any given datapoint to a cluster partition center weighted by that datapoint's membership value [14, 15, 16].

The mathematical description of the algorithm is described in the following discussion. For the Fuzzy C-means algorithm, the centroid of the cluster partition, which is the mean of all points in that cluster partition and weighted by the membership value of the points, is given by

$$center_k = \frac{\sum_x m_k(x)^f x}{\sum_x \mu_k(x)^f}. \tag{2.19}$$

The degree of class memberships is calculated as

$$\mu_{c_i}(x) = \frac{\sum_{j=1}^{k} \mu_{c_i}(x) \cdot \frac{1}{\|m - m_j\|^{\frac{2}{(f-1)}}}}{\frac{1}{\|m-m_j\|^{\frac{2}{(f-1)}}}}, \tag{2.20}$$

where m_1, m_2,...., m_k denotes the k nearest neighbors of x, and f is referred to as the fuzziness parameter. The value of f determines how heavily the distance is weighted when calculating the class membership. Looking at the equation, we can conclude that as the value of f increases, all the neighbors are weighted more evenly and when the value of f decreases, the closer neighbors are weighted far more heavily than those farther away. Consider a test point x divided into 2 partitions C_1 and C_2 using FCM, which has memberships μ_1 and μ_2 for the 2 clusters. The sum of the membership function values for a point in all clusters always adds up to 1: i.e.,

$$\mu_{1_x} + \mu_{2_x} = 1. \tag{2.21}$$

2.3 Classifiers

After the dataset is divided into homogeneous partitions, the next step involves the design of a classifier to evaluate if the division of the dataset had any effect on the classification accuracy. A large number of classifiers are available to implement this classification. The vital points that have to be evaluated before the selection of a classifier is made are the ease of implementation, training time, and performance. A few classifiers that are widely used are Neural Networks, KNN, and others. The Bayesian classifier was used to evaluate the classification accuracy of the methods explored in this thesis. The Bayesian classifier was mainly used due to its statistical accuracy and ease of implementation. Section 2.3.1 explains in detail the concept on which a Bayesian classifier classifies test points.

Bayesian classifiers belong to the class of crisp classifiers as the output results receive a single class label. The Bayesian implementation can be manipulated to include a fuzzy method in order to give some flexibility in classification of a test point. In this thesis, different combinations of training and testing approaches have been implemented to design the classifier to divide and classify the dataset. The dataset is still being divided by the DC and MDC degradation parameter values, and in addition they have different combinations of fuzzy and crisp training and testing methods. The various combinations that have been implemented are crisp training of the dataset divided by DC and MDC followed by crisp testing, crisp training divided by DC and MDC followed by fuzzy testing, fuzzy training divided by DC and MDC followed by crisp testing, and fuzzy training divided by DC and MDC followed by fuzzy testing. Sections 2.3.2 through 2.3.5 will discuss, in detail the approaches and implementation of the four approaches mentioned above.

For sake of simplicity of understanding and implementation, the division of data by a single DC and MDC value into two partition is being considered for experimentation and computing results. The same explanation and reasoning can be extended to the case for more than two partitions.

2.3.1 Bayesian Classifier

The Bayesian classifier has its roots in statistical pattern recognition. It is a simple probabilistic classifier based on applying Bayes theorem, which is based on independence assumptions. In simple terms, a naive Bayesian classifier assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature. "For example, a fruit may be considered to be an apple if it is red, round, and about 4diameter. Even though these features depend on the existence of the other features, a naive Bayes classifier considers all of these properties to independently contribute to the probability that this fruit is an apple" [12]. In spite of their naive design and apparently over-simplified assumptions, naive Bayes classifiers have worked quite well in many complex real-world situations. Depending on the precise nature of the probability model, the naive Bayes classifiers can be trained very efficiently in a supervised learning setting. An advantage of the naive Bayes classifier is that it requires a small amount of training data to estimate the parameters (means and variances of the variables) necessary for classification.

The Bayesian classifier assumes that the prediction of a character class can be modeled using any of the known distributions like Gaussian, Cauchy, etc. It must be noted that with the choice of different distributions, the discriminant function form will change based on the selected distribution. In this thesis, the Gaussian distribution was selected and it uses the center and spread of the feature vectors of the character class. The decision criteria can be influenced by the relative frequency of a particular class. The Bayesian classifier uses a discriminant as the metric to determine to which class a test character belongs. The following discussion will give details about the discriminant function and probability calculations used in evaluation by this classifier. The equation used for calculating the discriminant for each character class, i, is given by [13]

$$g_i(x) = \frac{-1}{2}(x - m_i)^T \Sigma_i^{-1}(x - m_i) - \frac{d}{2} ln(2\pi) - \frac{1}{2} ln|\Sigma_i| + ln(P(w_i)), \tag{2.22}$$

where m_i, d, and Σ_i are, respectively, the means of the character class under consideration, the number of features, which is considered a constant and covariance values for the character classes in the training dataset. The class, i with the greatest discriminant value, $g_i(x)$, for test point, x, is chosen.At everytest point, the mean and covariance values of each character class in the training dataset are used to evaluate $g_i(x)$, and the test point is assigned to the character class that yields the maximum value for this parameter.

In our case, all the class probabilities, $P(w_i)$, are equally likely because all classes have an equal number of characters in the test set. If the dataset is generated synthetically in such a way that the probability of selecting either character class in a data set is equal, this probability $P(w_i)$ can be ignored because it doesn't affect the relative values of Equation 2.22 for different i. The 2π term can be ignored because it is a constant value and will remain the same in the calculation of discriminant values of either class and thus can be neglected. Thus, Equation 2.22 can be simplified to

$$g_i(x) = \frac{-1}{2}(x - m_i)^T \Sigma_i^{-1}(x - m_i) - \frac{1}{2} ln|\Sigma_i|. \tag{2.23}$$

Equation 2.23 gives the hypothesis of aposterior probability of the test point belonging to a certain class. The Bayesian Classifier assigns the unclassified character to the character class that has a higher value from the application of Equation 2.23. This is what was used to decide to which character class to assign the unclassified test point.

2.3.2 Crisp Training

Crisp training refers to the training approach in which the training parameters for each character class are calculated for a rigid case where the point belongs to a definite cluster partition group. For ease of understanding the implementation approach, the case when a dataset is divided into two partitions has been elaborated. In this classifier training implementation, the training dataset is divided into 2 partition datasets by using DC and MDC degradation parameter values, respectively. Points will belong to one partition or the other, but not both. The training dataset points from the first partition are used to calculate the covariance matrices, Σ_i, and means, m_i, and then we proceed to calculate these values for the second partition. Calculating these parameters comprises the crisp training process. These parameters will then be used to calculate the discriminant function values when a test point is classified using Equation 2.23.

2.3.3 Fuzzy Training

Fuzzy training refers to the training approach in which the training parameters for each character class are calculated for a non-rigid case where the point may belong partially to multiple cluster partition groups. Every datapoint has a membership value in each of the resultant partitions whose value is determined by the probability of the point belonging to that partition. The total of memberships for a point in all partitions always adds up to 1. The membership function values are obtained from the fuzzy C-means clustering algorithm. In this implementation, the training proceeds similar to the method described in Section 2.3.2. The only change that we see in the training is that the features of the training dataset in each partition when divided by DC and MDC values are scaled with the membership values in the respective partitions. The weighted mean for each feature is obtained by scaling each moment feature of a datapoint with the membership values. This is done for every point of the training dataset. These scaled training dataset points from the first partition are used to calculate the covariance matrices, Σ_i, and means, m_i, and then we proceed to calculate these values for the scaled training points in the second partition. Calculating these parameters comprises the fuzzy training process. These parameters will then be used to calculate the discriminant function values when a test point is classified using Equation 2.23.

2.3.4 Crisp Testing

Crisp testing refers to the testing approach in which the unclassified test point is estimated based on determining the discriminant function value while rigidly belonging to a particular cluster partition or group. The test datasets are divided into two partitions based on a DC or MDC value. For testing individual test points in either partition, the discriminant value is calculated with Equation 2.23 using the training parameters from the corresponding partition in the training set. The discriminant values are calculated for the test point being a 'c' or an 'e'. The test point is assigned to the character class that has the larger discriminant value of the two values.

2.3.5 Fuzzy Testing

Fuzzy testing refers to the testing approach in which for every unclassified test point, all the determinant function values are calculated for all possible partitions and this is scaled with the appropriate membership function and a decision is made. Consider the case in which the training dataset is divided into two partitions C1 and C2. In this approach of testing, we do not divide the test datapoints into partitions using crisp degradation parameter values and subsequently use the corresponding training parameter values to calculate the discriminant function values. Instead, at every test point, four discriminant function values are calculated for each test point using training parameter values from both the partitions. The test patterns belong to either of the character classes ‘c’ or ‘e’ represented by *i*=1 for the test point of ‘c’ and *i*=2 for an ‘e’. A dataset that comprises of ‘c’ and ‘e’ and divided into 2 partitions C1 and C2 has 4 possible discriminant values for a test point. These 4 discriminant values are the test point belonging to partition 1 (C1) and being a ‘c’ i.e. *i*=1, test point belonging to partition 1 and being an ‘e’ i.e. *i*=2, test point belonging to partition 2 (C2) and being a ‘c’ i.e. *i*=1, and test point belonging to partition 2 and being an ‘e’ i.e. *i*=2. For calculating the four partition specific probabilities, the training parameters from the respective partitions of the training set are used. These discriminant values are scaled with the respective membership values of the test point in each of the two partitions. A modified discriminant value

$$g_{i-fuzzy}(x) = g_{i_{C1}}(x) \cdot \mu_1 + g_{i_{C2}}(x) \cdot \mu_2 \tag{2.24}$$

is calculated twice for each test point. In the equation, $g_{i-fuzzy}(x)$ is the total discriminant function value for the character point summed across both the partitions, and μ_1 and μ_2 are the membership values for the test point character in C1 and C2, respectively. Initially, the discriminant function of the test point of belonging to character class ‘c’ and partition 1, i.e. $g_{i_{C1}}(x)$, followed by being a ‘c’ and belonging to partition 2, i.e. $g_{i_{C2}}(x)$, is evaluated. These values are scaled with the membership function values μ_1 and μ_2 in the respective partitions. This equation value is similarly evaluated for the test point belonging to character class ‘e’. The resultant scaled discriminant function values of characters ‘c’ and ‘e’ in C1 and C2 are added to get the resultant discriminant values of the test point being a ‘c’ and an ‘e’ in both partitions.

The larger of the two values decides the resultant character class of the test point.

Equation 2.24 is a slight variation of Equation 2.23 used for evaluation in crisp testing. In the crisp classification case, a point belonging to partition 1 will have membership of 1 in C1 and 0 in C2 unlike a fuzzy case in which test points have partial memberships where membership function μ has values between 0 and 1 but never 0 or 1. Thus, in the fuzzy case, the probability calculation before a test point is assigned does not just limit itself to one partition that is determined crisply but values are calculated by considering the test points possibility of being in both partitions.

CHAPTER 3

EXPERIMENTS

The tests that were implemented in this thesis were motivated by the goal to explore and answer the following six questions. These questions are:

1. Did the division of the dataset improve the accuracy of classifying the dataset?

2. Is MDC a better parameter to partition the dataset than DC?

3. If the dataset was divided by the incorrect DC and MDC values, how does it affect the performance?

4. What is the reasonable number of partitions into which a dataset should be divided?

5. What is the error associated with estimating the wrong DC and MDC parameter for a character?

6. Does the use of a fuzzy approach of classification offer any improvement in performance over the crisp approach?

Before these questions can be explored, the first step was generating synthetic data similar to degraded scanned characters. The data used to explore this is described in Section 3.1. Some of the characters produced will vanish, and some will be excessively degraded. The degraded synthetic dataset generated has to be visually inspected to decide what is a permissible degradation that can be inherent in a training character. This decision is based on visual appearance of the degraded character. In Section 3.2, the preprocessing of the data, which includes filtering for removing isolated salt and pepper noise and limiting exploration to characters with a minimum number of pixels, will be explained.

After the dataset was generated, the datapoints that varied in character stroke thickness were grouped into similar featured classes using the Isodata clustering algorithm. This clustered data was then partitioned into smaller homogeneous datasets using the edge spread degradation parameters DC and MDC as the division parameters. This was done in order to facilitate the generation of smaller training datasets with similar degradations. Finally, this divided data was used to train and classify datasets to verify if the partitioning made any change to the classification accuracy compared to an undivided dataset. Subsections 3.3.1 through 3.3.3 discuss the Isodata clustering, boundary fitting, and division and classification tests. With all the requirements fulfilled to analyze the tests for this thesis, the following briefly discusses the implementation details.

To answer the first two questions, tests were done on the unpartitioned dataset as well as the dataset divided by an exhaustive set of DC and MDC values, each with the subsequent classification details of which are given in Section 3.3. Question 3 analyzes what happens if we use an incorrect value to divide the dataset after we do the clustering or we just make an educated guess on the parameter to partition the division value. Section 3.5 discusses the implementation of accuracy analysis done for the different values of edge spread degradation parameters and how that affects the accuracy as we move across the clusters.

Question 4 explores whether there is an upper limit on the final number of partitions. Division of the dataset into more partitions to improve the classification may not always hold true and there might exist a limitation on this approach. Section 3.4 discusses how the selection of the final number of partitions that a data set can be divided into was explored.

Questions 1 through 4 analyzed classifier performance based on the assumption that the points were assigned to the correct partitions. The training datapoints are divided into groups based on the DC and MDC values calculated from the degradation parameter estimated from the character. Questions 5 and 6 analyze what happens when the degradation parameters estimated for a character are incorrect. The effects as well as possible implementations of solutions to overcome this problem are discussed in Section 3.6.

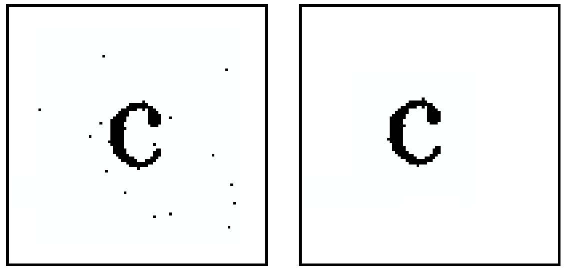
3.1 Dataset

The scanner model was used to synthetically generate datasets comprised of characters ‘c’ and ‘e’ with varying PSF widths w and binarization threshold θ. In this case, only the characters ‘c’ and ‘e’ were chosen in the experiments because they look very similar and hence statistically have similar properties.Thus, differentiating between them poses the greatest challenge to modern OCR engines. Once the idea and method suggested in this thesis yield good classification accuracy for ‘c’ and ‘e’, the same concept can be extended to datasets ‘a’ through ‘z’ in different fonts and font sizes.

The dataset used in the experiments in this thesis contains a total of 100,000 characters. The characters that are used in the experiments have been generated by using the degradation model [11] with random Gaussian noise included in the data generation to account for the noise that a character is degraded by in real-text scanning. The characters that are generated are 12 point, 300 dpi, sans serif font, lowercase characters ‘c’ and ‘e’. The PSF width used for blurring ranges within the limits 0.2 to 3. Scanning introduces noise in the resultant transcript of scanned characters in digitized form. This noise has to be accommodated or simulated while the classifier is trained to get better classification. It can be seen that the noise pixels introduced in scanning are generally around the edges of the scanned character and almost zero or no noise pixels around the character that is scanned. While generating the character dataset, Gaussian noise with standard deviation up to 0.15 was added in the generation. The blurred characters with noise included that have been generated have to be thresholded to get the final character image. The threshold is also chosen randomly between the limits 0.05 and 0.95. Any character pixel value below this threshold value is considered to be white or background.

After thresholding, the character is passed through a filter that removes all the salt and pepper noise that is not directly associated with the character and is present in the image background. This pre-processing is done because the moment features are to be calculated on the character and not separate disjoint noise. The filter to remove salt and pepper noise looks for standalone single pixels that are present with a gap of 1 pixel around them and removes them. At times, the noise pixel is attached to the character pixel and hence cannot be filtered by this approach. This noise is referred to as edge noise and is not removed in this thesis. Looking at Figure 3.1(a), which has noise, it can easily be concluded that the character generated is noisy with uncorrelated noise. Filtering has been done to ensure that we are only considering the noise that exists at the character corners or along the boundary of the character stroke so that they visually resemble the noise introduced in a character by an actual scanning process. Figure 3.1(b) shows the character ‘c’ without salt and pepper noise. There is no skew added to these generated characters as the only degradations that are being considering in this thesis are edge spread degradation parameters DC and MDC introduced due to scanning operation. Features can be calculated that are skew independent.

The synthetic data images with the majority of salt and pepper noise removed are then used to extract the features used for classification. The features chosen are moment features. The moments can be defined as features of an object that allow a geometrical reconstruction of an object. The general definition of moment features and central moment



(a) (b)

Figure 3.1: (a) Character ‘c’ with noise, (b) filtered image with most of the noise around the image removed

features for a gray value function *f(x,y)* of an object are given by

$$m_{p,q} = \int\int x^p \cdot y^q \cdot f(x,y)dxdy, \tag{3.1}$$

and

$$\mu_{p,q} = \int\int (x-\bar{x})^p \cdot (y-\bar{y})^q \cdot f(x,y)dxdy. \tag{3.2}$$

where $\bar{x}$ and $\bar{y}$ are the moment features $m_{0,1}$and $m_{1,0}$. This integration is calculated over the area of the object. If we use binary images, the gray value function *f(x,y)* becomes

$$f(x,y) = b(x,y). \tag{3.3}$$

Moments are generally classified by the order of the moments. The order of a moment depends on the indices p and q of the moment $m_{p,q}$. The sum p + q of the indices is the order of the moment $m_{p,q}$. Thus, the zero order moment, i.e. (p,q)= (0, 0), is given by

$$m_{0,0} = \int\int b(x,y)dxdy. \tag{3.4}$$

The zero order moment describes the area of the object, which in this case is the count of the number of pixels in the image. The first order moments, i.e. (p,q) = (1,0) or (0,1), are given by

$$m_{1,0} = \int\int x \cdot b(x,y)dxdy, \tag{3.5}$$

and

$$m_{0,1} = \int\int y \cdot b(x,y)dxdy. \tag{3.6}$$

The first order moments contain information about the center of gravity of the image.

In this thesis, the moment features that are extracted are $m_{0,0}$, $\mu_{0,2}$, $\mu_{1,1}$, $\mu_{0,3}$, $\mu_{2,0}$, $\mu_{3,0}$, $\mu_{2,1}$, and $\mu_{1,2}$. These 8 moments will be the features used to train and test the classifier. These 8 moment features are calculated for each of the characters in the dataset.

3.2 Analysis of Cutoff Selection for the Number of Pixels in Generated Characters

With the degradation being simulated, character strokes can get very thin and sometime characters can vanish all together. Equation 2.15 explains mathematically the condition under which a scanned stroke may completely disappear. Thus, it becomes necessary to decide what is a permissible degradation for a character in the dataset so that it still has significant analysis capability. This is done by deciding how many pixels the generated synthetic degraded character must have relative to the ideal character. This is a vital decision that sets the limits on the level of degradations that are used in training the classifier. Degraded characters with negative DC or MDC values can thin strokes to just a few pixels width, or make them totally disappear. The different variations in character stroke widths can be seen in Figure 3.2. In case there are only a very few pixels, it is insufficient or impossible to conclude even visually if it is a ‘c’ or ‘e’, which makes it difficult if not impossible to recognize using recognition algorithms. We need to select a value for the minimum number of points a character must maintain. This decision was made after visually inspecting an ideal character and different variations of it with varying numbers of black pixel counts.

In order to do this analysis, an ideal character using a PSF width of 1 and thresholded at 0.5 was generated. The number of black pixels in this ideal character was calculated. Synthetic characters that have the total number of pixels varying between 5% and 150% of the ideal character pixel count were generated. These generated characters were visually inspected to decide which of these characters are visually identifiable and hence can be considered part of the dataset.

In earlier work [8], characters with as few as one black pixel were included in the dataset. The intuitive feeling before we start off with analyzing the cutoff value selection is that the more pixels we have, the better we can conclude visually what character we are seeing. This in turn leads to more comprehensive features being fed to the classifier. This ensures minimal misclassification. However, since the effect of degradation on recognition is being evaluated, characters that are largly eroded are also of interest. In most cases, it can be noticed that there are always partial characters but never just a single dot, few dots or clusters of very few pixels. The worst case that we encounter is probably a partially eroded printed character that leads to a partial scanned character. Figure 3.2 shows characters ‘c’ and ‘e’ with cutoff values between 5-150% on number of pixels relative to an ideal character.

As we successively lower the pixel cutoff as we go from 100% down to 5%, we can see from the character plots in Figure 3.2 that in the case of a 5% cutoff, a few characters show up just as a few dots without any definite shape and hence we cannot visually conclude what character it is. In case we extract the moment features from such characters and used them to train and classify, we will not be able to get very good classification due to lacking data sufficiency. Hence, we need to increase the cutoff selection to get visually classifiable characters. The selection of cutoff is totally a visual choice. The data is generated for a particular cutoff value, data is visually inspected for data sufficiency and then a value is selected. After looking at Figure 3.2, we concluded that selecting 10% cutoff will produce a good dataset with manageable degradations.

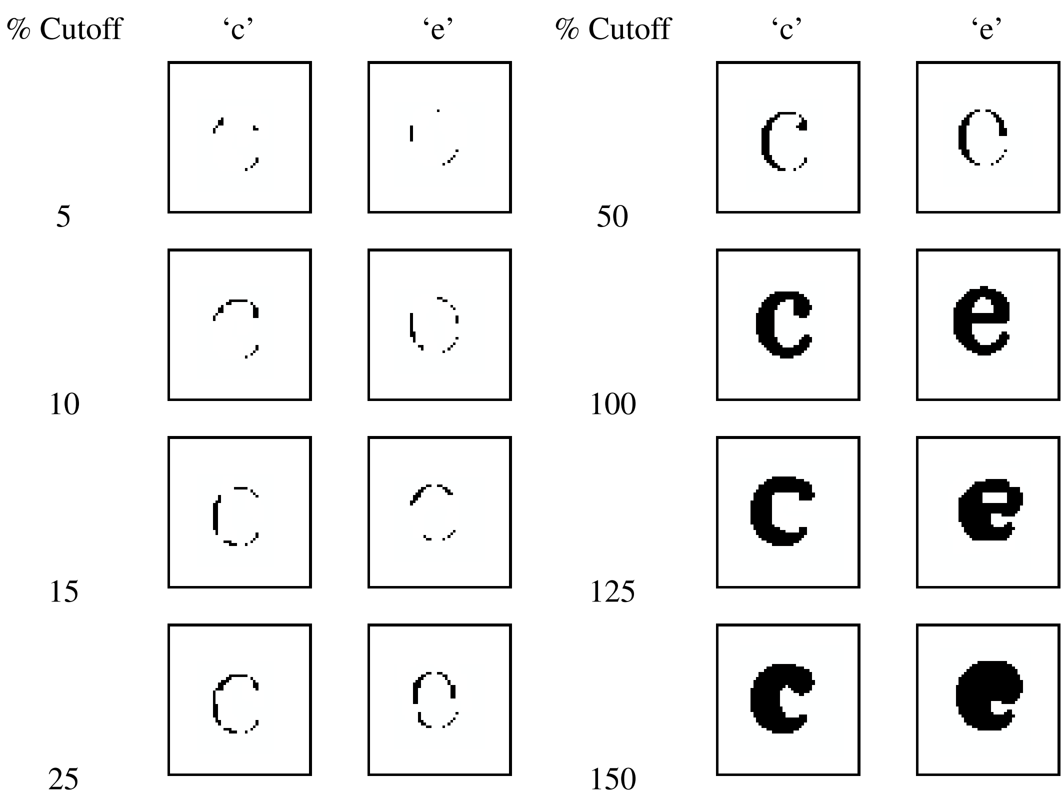


Figure 3.2: Characters ‘c’ and ‘e’ are shown with limits of 5, 10, 15, 25, 50, 100, 125 and 150%.

3.3 Implementation Details to Validate the Tests

The same data are used for all experiments. Three parameters that are calculated from the training file and used to classify the test points are the class conditional means and covariances and the root mean square (RMS) values for each feature. The mean and covariance values were used to calculate the probability value of each test point being any of the character classes to classify them. The RMS value is defined as a statistical measure of the magnitude of a varying quantity. The moment features calculated for the character points are not in the same range (i.e., a few features are very small while others features are large). In order to calculate the 1 nearest neighbor from the mean, equal importance has to be given to each feature of the 8 to estimate the nearest neighbor. This is possible only if the value of all the features are comparable which is achieved by getting them in the same relative scale. RMS values are needed so that the test points can be normalized based on the training set values. The Bayesian classifier is used to classify the datapoints in all the experiments.

The 10 fold cross validation approach is used for all experiments. After testing all the test points, error values of the classification results were used to calculate the weighted percentage classification error. In this calculation, the errors in each partition are scaled with the weight of that partition (i.e., the total datapoints).

The ultimate goal in using an OCR engine is to get minimum error in the final digitized transcript. This can only be achieved if the training is done in such a way that most of the test patterns to which the OCR engine will be exposed are used in the training phase. The idea of dividing the non-homogeneous dataset into smaller homogeneous sets based on division by the DC and MDC degradation parameters is a very effective method to train the classifier to get high classification accuracy. To maximize utilization of this idea, the main challenge is in estimating what value needs to be used to divide the dataset. The decision on the values of DC and MDC to partition the dataset was strictly based on visual inspection of the cluster plot and fitting a boundary between the cluster partitions to estimate the values. However, we must not rely on visual decision alone. Thus, we confirm/evaluate that validity of estimating the cluster boundary by visual decision by doing an exhaustive search of cluster partition boundaries division and classification to evaluate the classification performance. Thus, tests were done with all possible DC and MDC values to estimate the best values to divide the dataset before training and classification. The details of this approach are given in Section 3.4.

At the beginning of the chapter, six questions to be explored in this thesis were listed. To analyze the first and second question, the following 3 steps are needed: (1) generate a cluster plot for different numbers of partitions like 2, 3, 4, etc., (2) fit by visual inspection the best DC and MDC boundary values, and (3) use these DC and MDC values to divide the dataset and classify data using the Bayesian classifier. To analyze the third question, the steps need to be: (1) generate data, (2) select a range of DC and MDC values that cover the complete range of values seen in the generated data, (3) use the single DC and MDC values or a combination of DC/MDC values, depending on the 2 or 3 partition case, from amongst the range of DC and MDC values to repeatedly divide the dataset and classify by using Bayesian classifier, and (4) evaluate the classification accuracy across cases and plot the accuracy curve. The following subsections will give details on each of the steps followed.

3.3.1 Clustering

A clustering algorithm tends to group points into groups or partitions based on a certain relation or similarity between the points. In this case, the relation that is evaluated for grouping is the similarity in moment features. This is a result of the strong similarities in points belonging to the same cluster partition in their visual appearance. This similarity within partition points is seen across all the resultant partitions. The sample plot of characters with variation of PSF width w and binarization threshold θ in degradation space with DC lines drawn across it is shown in Figure 3.3. If we inspect the figure closely, it can be noted that the characters in the lower-right part of the plot are very thick and easily visible while characters to the top right have a very faded appearance and are barely visible. The character stroke width gets bigger as we move from top to bottom along the plot. It can also be seen clearly that in the areas enclosed by the DC lines, the general appearance of the character remains the same for 'c' as well as 'e' and that the DC lines split the entire non-homogeneous plot into 4 distinctively separate parts with high homogeneity in each part. Similar groupings can be seen if the dataset is clustered and MDC lines are fitted. Hence, after the dataset has been created, Isodata clustering was done to get homogeneous subsets of the dataset.

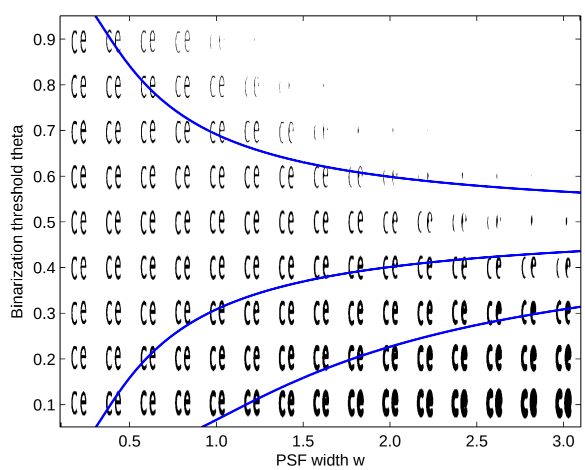


Figure 3.3: Sample plot of characters with variation of PSF width w and binarization threshold θ in degradation space with DC lines drawn, x-axis is PSF width, y- axis is binarization threshold θ.

Moment features were calculated for each of the characters and were used to cluster the dataset. The different number of partitions as well as different combinations of data were clustered and plotted. In each of the cluster plots, the x –axis was the PSF width and the y-axis was binarization threshold. The members of different cluster partitions were indicated by ‘x’ and ‘o’ marks and also using different colors to be easily distinguishable. A few cluster plots are shown in Figures 3.4-3.7.

The dataset with different values of cutoff on the number of pixels generated and divided into two partitions is shown in Figure 3.4. All of these plots have approximately the same number of points in the lower cluster partition. As the cutoff to consider a datapoint in the training set is lowered, we see more points clustered at the top of the cluster plot. It is evident looking at Figure 3.4 that as the black pixel count cutoff to consider a datapoint in the training dataset is lowered successively from 100% to 50% all the way through 5%, the cluster plot had more and more points in the upper-right part of the degradation space. The average character in the degradation space is thin and there are many of them with this appearance. Thus, in the C-Means, the mean calculation of the cluster is driven by these average points and thus addition of any new faded characters to this cluster does not produce an appreciable change in the cluster center of this partition. This is a problem inherent in the C-Means clustering algorithm and the use of other clustering algorithms may handle this situation.

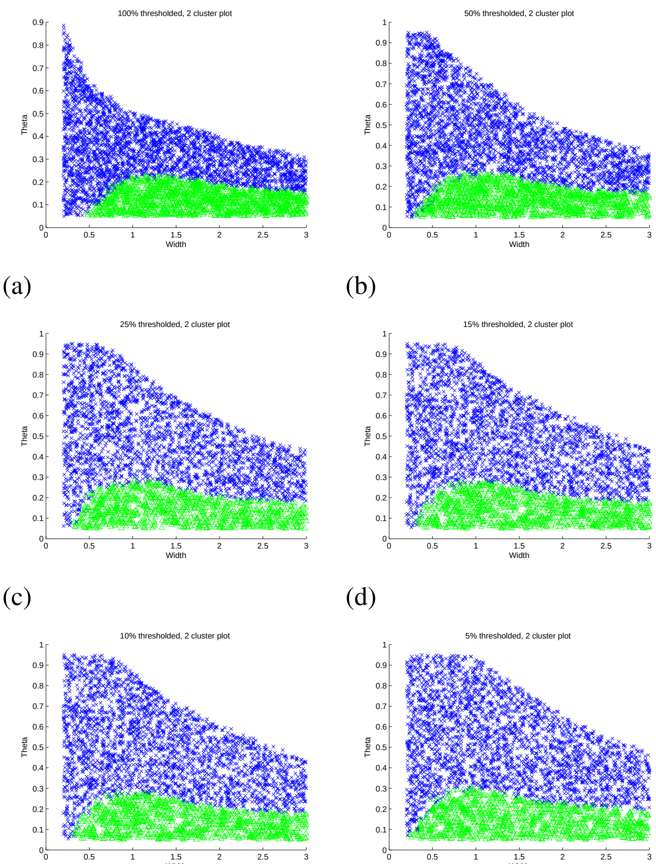
Looking at Figure 3.3, it can be seen that a ‘c’ and ‘e’ with the same degradation parameters do not look similar. The characters ‘c’ and ‘e’ with width and threshold 0.65 and 0.6, respectively, are distinguishable. These ‘c’ and ‘e’ look more similar to respective ‘c’ and ‘e’ with width and threshold 1.5 and 0.5, respectively. These similar looking characters belong to the same partition when divided by the DC lines. Also, the ‘c’ and ‘e’ in every partition have more similarity with the ‘c’ and ‘e’ in the same partition than with other partition characters. Thus, the goal in dividing the dataset by DC and MDC lines is to achieve this division of large non-homogeneous dataset into smaller homogeneous partitions with more similarity in appearance and thus features.

The data was again clustered using the Isodata clustering algorithm. Different combinations of data were used to do clustering. In the first case, the ‘c’ and ‘e’ were separated from the dataset, and in the next case, the dataset contained the ‘c’ and ‘e’ mixed together. Cases of both 2 and 3 partitions were considered. The 2 partitions plotted for characters ‘c’ and ‘e’ can be seen in Figures 3.5(a) and (c). We can clearly see that the cluster partitions are disjointed when we consider the separate character ‘c and ‘e’ cluster plots as seen in Figures 3.5(a) - (d). In the next case, the characters were mixed and clustered. The 2 and 3 partitions plotted for characters ‘c’ and ‘e’ mixed can be seen in Figures 3.5(e) and (f).

The features of the plot led to the conclusion that mixing the character datasets and then clustering causes the partitions to mix with each other around the border, separating them as seen in Figures 3.5(e) and (f). This mixing of cluster partitions can be attributed to the fact that a few typical character points affect the way the partitions are formed. A highly degraded character ‘e’ may lose its horizontal bar, making it have moment features more similar to a ‘c’, and hence they will be grouped together causing mixing of characters in partitions and vice versa. When such a point is considered, the new mean of the cluster partition is updated incorrectly and the further assignment of points to cluster partitions causes the clusters to mix and thus overlap.

3.3.2 Fitting DC and MDC Boundaries

After clustering the dataset, the DC and MDC degradation parameters were used to separate the cluster partitioned data into more homogeneous partitions that could be used to train



(a) (b)

(c) (d)

(e) (f)

Figure 3.4: 2 cluster plot with cutoff on number of black pixels relative to an ideal character being (a) 100%, (b) 50%, (c) 25%, (d) 15%, (e)10%, (f) 5%.

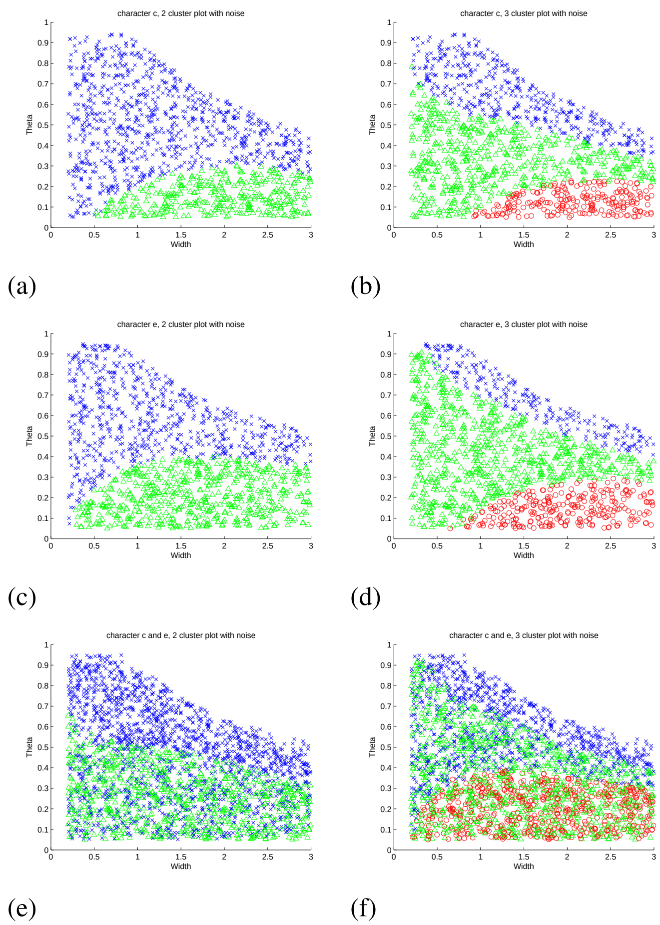


Figure 3.5: Clustering of character features by width,theta (a) character*c* divided into 2 partitions, (b) character*c* divided into 3 partitions, (c) character*e* divided into 2 partitions, (d) character*e* divided into 3 partitions, (e) mixed charactesr*c* and *e* divided into 2 partitions,(f) mixed charactesr*c* and *e* divided into 3 partitions.

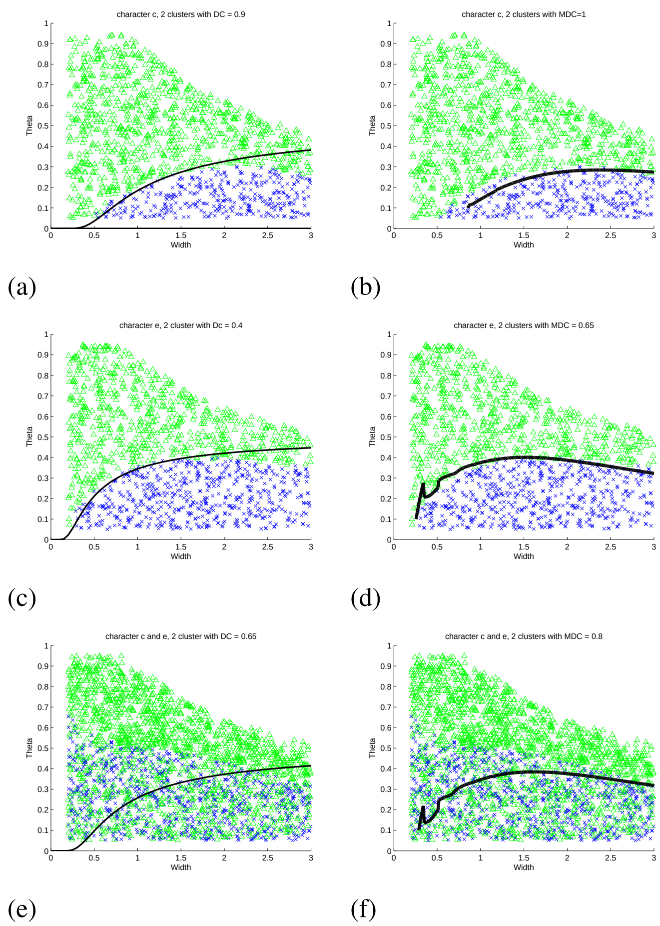


Figure 3.6: 2 cluster partitions (a) character*c* with DC = 0.9, (b) character*c* with MDC = 1, (c) character*e* with DC = 0.4, (d) character*e* with MDC = 0.6, (e) mixed charactesr*c* and *e* with DC = 0.9,(f) mixed charactesr*c* and *e* with MDC = 0.8.

the classifier. Figures 3.6(a)-(f) show cluster plots of the 2 partition cases for the character ‘c’, ‘e’, and mixed ‘c’ and ‘e’ characters. The individual cluster partition boundaries for standalone character ‘c’ and ‘e’ for the 2 and 3 partition cases were noted and they were averaged to estimate the DC and MDC boundary for the mixed dataset.

The DC values for ‘c’ and ‘e’ are 0.9 and 0.4, and MDC values for ‘c’ and ‘e’ are 1 and 0.65, respectively. Assuming that the DC and MDC boundary for a mixed dataset of these characters can be calculated by taking the simple average of the individual DC and MDC values of ‘c’ and ‘e’ datapoints leads us to DC = 0.65 and MDC = 0.8 for the average case boundary values. Looking at Figures 3.6(e) and (f), we can conclude that the value of average DC and MDC when used as the boundary of the mixed dataset was not exactly the best fit boundary between the cluster partitions.

The 2 and 3 cluster partition plots for the mixed ‘c’ and ‘e’ dataset with the DC and MDC boundaries fitted are shown in Figure 3.7. The best fit DC and MDC lines are drawn that form the intercluster boundary for the 2 and 3 cluster partition cases and these boundary values are noted. The actual mixed cluster is plotted when we estimate the DC and MDC boundaries formed; they are 0 and 0.01, respectively, for the 2 partition case. Thus, to get the appropriate best fit, the characters were mixed followed by clustering and then the DC and MDC boundaries were fitted between the cluster partitions.

It can be concluded by looking at the 2 and 3 cluster partition case with the MDC lines drawn shown in Figures 3.7(b) and 3.7(d) that the MDC value as a boundary between the cluster partitions is a better fit than the DC boundary shown in Figures 3.7(a) and 3.7(c). Thus, if we fit the DC and MDC boundaries, we get the separation between the cluster partitions. This causes similar looking characters to group together, thus dividing the non-homogeneous dataset into many homogeneous sets. These values will be used to divide the dataset to train the classifier and test the data to verify the accuracy of the classification and check if we actually get better classification accuracy.

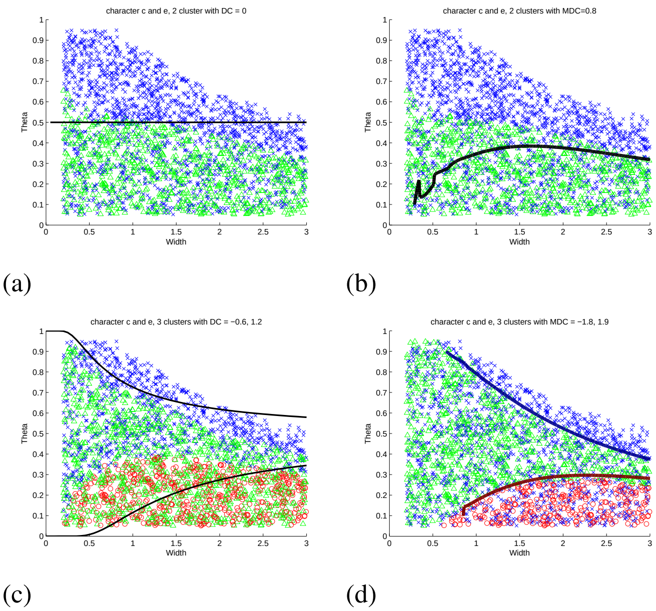


Figure 3.7: Character *c* and *e* mixed dataset (a) divided into 2 partitions and divided by DC partition, (b) divided into 2 partitions and divided by MDC partition, (c) divided into 3 partitions and divided by DC partition, (d) divided into 3 partitions and divided by MDC partition.

3.3.3 Partitioning and Classification

After the values of DC and MDC that best fit the boundary between the cluster partitions chosen in Section 3.3.2 are used to divide the datasets, the Bayesian classifier was trained on each of these partitions. The test data was evaluated on the same set of partitions and the total accuracy was calculated based on relative dataset sizes. In this calculation, the errors in each partition were scaled by the percentage of the total datapoints in that partition. Testing was also done to calculate the classification accuracy when there was no partition in the dataset.

3.4 Decision on Number of Cluster Partitions and Cluster Boundaries

While analyzing how many cluster partitions to use to divide the data, one concern is consider the practical implementation, the associated cost and effort for that case. The division of data into too many cluster partitions will not only make the grouping decision complicated, but also cause fictitious grouping of datapoints, while a lower number of cluster partitions will cause forcible grouping of not too closely related datapoints due to the sheer lack of options available to group. Hence, a tradeoff needs to be made between the number of cluster partitions and practical implementation considerations. The dataset was clustered into 2-5 cluster partitions. The cluster plots are shown in Figure 3.8.

Looking at Figure 3.8, it can be seen that beyond 3 cluster partitions, there are clear boundaries between partitions, but there is no DC or MDC boundary that can separate the partitions without overlap between inter partition points. Thus, further division by DC or MDC will not result in enabling any futher division of the dataset into homogenous partitions. This difficulty in turn leads to problems in training the dataset on these regions to improve the accuracy of the resultant classification of the degraded dataset. Thus, it can be concluded that if the dataset is divided into more than 3 partitions, the resultant partitions are not completely separable by DC or MDC and it is difficult to fit a boundary between the partitions. Thus, in this thesis, only the 2 and 3 partition cases were considered.

3.5 Exhaustive Cluster Classification Accuracy Analysis

The problem of estimating the optimal DC and MDC cluster boundary for a dataset can be solved by doing an exhaustive division by DC or MDC values of the dataset and calculating the resulting classification accuracy in both the 2 and 3 partition cases. In the case of the dataset divided into 2 partitions, the DC and MDC cluster boundary values were moved in

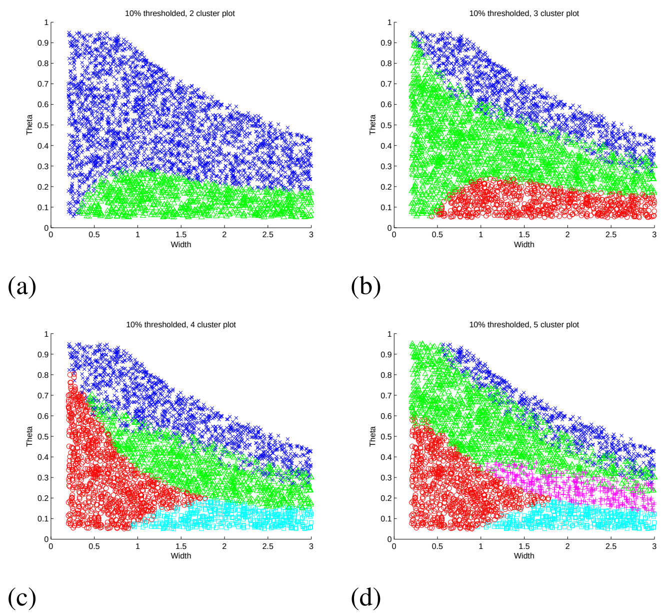


Figure 3.8: 10% thresholded character *c* data (a) divided into 2 partitions, (b) divided into 3 partitions, (c) divided into 4 partitions, (d)divided into 5 partitions.

such a way that they completely spanned the range of DC and MDC values of the data in the cluster plot. The partitions were made in such a way that they started with the first partition having either one point or very few points across the test sets in each of the 10-folds and all or almost all the points in partition 2. The values of DC and MDC were gradually increased so that partition 1 kept growing in the number of points from the initial one point or few points assigned to it until the point where it had maximum points while partition 2 gradually shrank. The classification accuracy when the test set is divided by the values of DC and MDC was calculated and noted at each step.

The accuracy curves for the 2 region case are shown in Figures 3.9(a)-(b). The accuracy curve has the x-coordinate as the DC and MDC values and y-coordinate as the accuracy for the 2 region case. The accuracy with no boundary division is shown as referenced as a horizontal line in the plot of accuracy achieved by dividing into partition by DC and MDC.

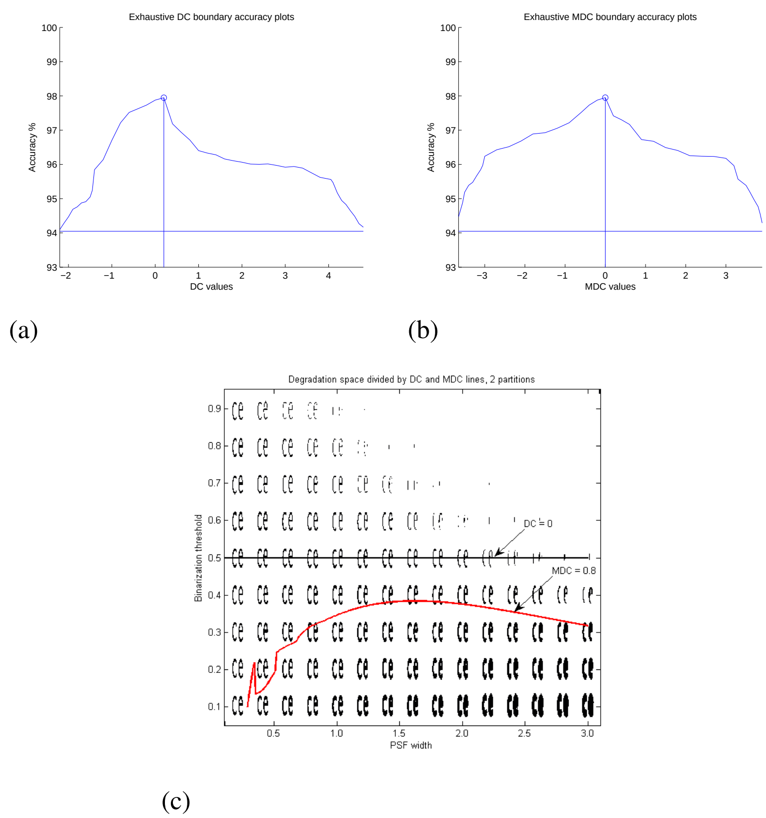
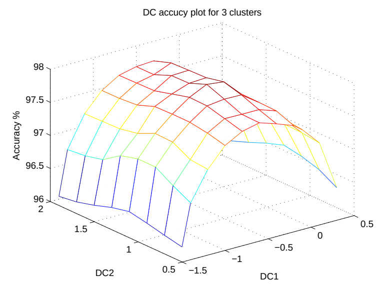


Figure 3.9: Accuracy plot, exhaustive division of characters *c* and *e* mixed dataset (a) by DC for 2 partitions, (b) by MDC for 2 partitions, (c) Samples of ‘c’ and ‘e’ throught the degradation space. DC and MDC lines are shown for the optimal values for 2 partitions

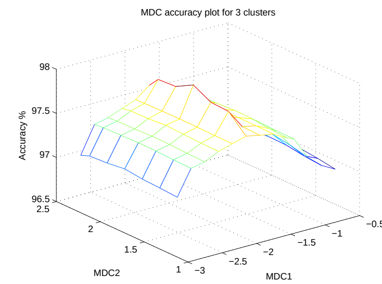
It must be noted that this value of accuracy for the no-division case remains unaffected as DC and MDC boundaries change. The partitioned accuracies are always greater than the unpartitioned accuracy. The plots have peaks at the values DC = 0 and MDC = 0.8, respectively. The effects of these boundaries on samples from the degradation space are shown in Figure 3.9(c) with the optimal boundaries superimposed. The accuracy decreases as we move away from this value in either direction of DC or MDC values.

The same procedure is repeated for the dataset divided into 3 regions and classified. The dataset in this case is divided into 3 regions using two DC and MDC values and the same iterative process is done as was in the case of 2 partition analysis. The accuracy plot for the 3 region case is shown in Figures 3.10(a) and (b). In this plot, the DC1 and DC2, and MDC1 and MDC2 values are, respectively, the x and y coordinates and the accuracy of the 3 partition classification case is the z coordinate. The general shape of the accuracy curve is similar to the accuracy plots of the 2 partition DC and MDC cases. The only significant difference from the 2 cluster plots is that in the case of the 3 region plot, the point at which we see maximum accuracy is more like a ridge than a peak for division by DC as well as the MDC case. The peak of the ridge is seen at the point where the values of DC are -0.6, 1.2 and MDC are -1.8, 1.9 respectively as can be seen in Figures 3.10(a) and (b). Figure 3.10(c) shows characters ‘c’ and ‘e’ in the degradation space divided into 3 partitions. Looking at the partitions, we can conclude that the DC and MDC values divide the entire data into 3 partitions with the first partition having highly degraded characters that are barely visible, the second partition having average thin characters, and the third partition having thick characters.

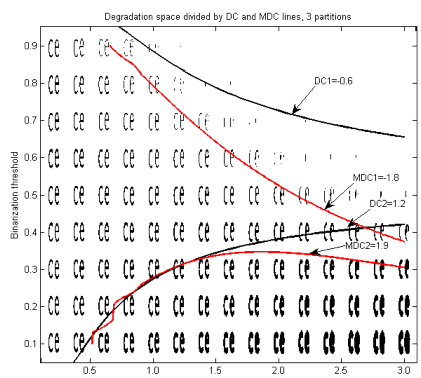
We see no definite peak but a ridge in the case of the 3 regions cases for DC and MDC. The reason for this can be understood looking at Figure 3.10. If we are at the top of the degradation space plot, the characters at this point are highly degraded. The features



(a)



(b)



(c)

Figure 3.10: Accuracy plot, exhaustive division of characters *c* and *e* mixed dataset (a) by DC for 3 partitions, (b) by MDC for 3 partitions, (c) samples of ‘c’ and ‘e’ throughout the degradation space. DC and MDC lines are shown for the optimal values for 3 partitions

extracted from these degraded characters change rapidly with changes in the degradation parameters and hence the classification rate is strongly affected by the boundary location. For lower threshold (large DC and MDC), the degradation effect looks less noticeable in the characters. This indicates that the character is more visually recognizable and easier to classify with a good accuracy for a wider range of DC and MDC boundary values. Thus, we see no specific peak but a general ridge for the classification rate after division.

3.6 Fuzzy vs Crisp Boundaries and the Need for It.

It is possible at times that the degradation parameters may have been estimated incorrectly. In a crisp classifier approach, this will result in the test point being assigned to an incorrect group. This effect is more predominant in points that lie along the crisp cluster partition boundary. Consider the 2 partition case for simplicity of understanding the concept. In the crisp approach of classifier implementation, once a point has been assigned to a partition group, it becomes part of that group with no flexibility. Thus, in this case, there is a very good chance of improper assignment of a test point to a character group even if the difference between group classes is very small at the border. This is a result of incorrect training parameter values used to determine the character class of an unclassified test point. In contrast, in a fuzzy classifier approach, test points are not rigidly associated or tied to any particular group or partition; they have partial membership in all groups. In this approach, when a test point is being classified, the membership value of that test point of being each of the character class in both the partitions is calculated. Thus, the initial grouping of a test point in an incorrect partition due to incorrect parameter estimation does not affect the final classification as much. For these reasons, the fuzzy classifier has been implemented.

Table 3.1: Classification results for 2 partitions

Training Method	Crisp Testing	Fuzzy Testing
Crisp (divided by DC)	97.94	97.60
Crisp (divided my MDC)	97.94	98.08
Fuzzy (divided by DC)	88.42	89.34
Fuzzy (divided by MDC)	92.89	93.23
No Boundary	94.08	NA

Different training and testing methods were experimented with in order to achieve better classification accuracy. Fuzzy and crisp methods of training and testing were implemented as described in Subsections 2.3.2-2.3.5 with different combinations with the results shown in Table 3.1 for the two partition case. The classification rate of crisp training with fuzzy testing is better than crisp training with crisp testing. This is because crisp training associates definite training parameters that can be used to classify each test point rather than a fuzzy approach where there is ambiguity in training parameters due to the fuzziness criteria. The results show that the fuzzy training did not prove to be a very good approach. Rather than giving flexibility on the features used, the fuzzy training resulted in a lack of definition of each partition. The fuzzy method is a good approach to be implemented in testing because instead of just assigning a test point to a character class by testing it with pre-determined training values that are decided rigidly, we consider a test point to have numerous possibilities in assignment with regards to cluster partitions and we make a decision based on evaluation and scaling of all possible value. Across all the combinations of training and testing, using MDC as a parameter to divide the dataset yields a marginally better classification rate than DC. Looking at the table, we can conclude that the best classifier performance of 98.08% is achieved when the crisp training and fuzzy testing approach is implemented for the dataset divided by the MDC degradation parameter.

Table 3.2: Classification results for 3 partitions

Training Method	Crisp Testing	Fuzzy Testing
Crisp (divided by DC)	97.90	98.10
Crisp (divided my MDC)	97.91	98.93
Fuzzy (divided by DC)	90.20	90.01
Fuzzy (divided by MDC)	90.34	90.52
No Boundary	94.08	NA

Table 3.2 contains the classification results for the 3 partitions case for the different combinations of training and testing. It can be concluded that even in this case, the accuracy achieved by using the crisp approach to train and fuzzy approach to test the dataset divided by MDC again yields the best accuracy, this time with an accuracy of 98.93%. The fuzzy training is still not a very good training approach and is more effective as a testing method in the classifier implementation. The classification result for all the implementations implies that the MDC is a marginally better parameter to divide the dataset than DC.

Looking at Tables 3.1 and 3.2, we can see that the crisp training and fuzzy testing results have an improvement in performance for the case of 3 clusters over 2. The T Statistical validation test was used and it was verified that this difference in classification accuracy improvement is not statistically significant for crisp training and fuzzy testing for division by DC but is statistically significant for division by MDC as the accuracy increases from 98.08% to 98.93%. The crisp training and crisp testing results for the 2 and 3 partition cases for the dataset divided by DC and MDC is very similar. This can be attributed to the fact that incorrect assignment of points to partitions during the training phase is still not being handled in this approach. The fuzzy training approach is not a very good approach to train the classifier across the 2 and 3 partition cases irrespective of the division by DC or MDC. The fuzzy training and fuzzy testing for the dataset divided by MDC into 3 clusters has lower classification accuracy than the case where the dataset is divided into 2 partitions and this difference is statistically significant.

CHAPTER 4

CONCLUSION AND FUTURE WORK

This thesis modeled the scanning degradation effects when a bilevel image is scanned. The effect of scanning isolated strokes as well as combinational edges was analyzed and the DC and MDC degradation parameters were developed. The main degradations during scanning are caused due to blurring, which is modeled by a PSF. Due to the inability to get a real-life character document with all the scanning degradation variations and also due the high cost associated with the calibration of degradation in such documents, the characters with degradations were synthetically generated using the scanner model. A synthetically generated dataset of 100,000 points of random characters 'c' and 'e' in 300 DPI with Gaussian noise having standard deviation 0.15 added to it was used in the tests. The characters 'c' and 'e' were specifically generated to be present in the training dataset because they look visually similar and pose the biggest challenge to the classifiers. These characters were generated with varying PSF width and binarization threshold. This dataset was then filtered to remove the salt and pepper noise. Filtering was done to only include the edge noise and remove all isolated noise pixels to exactly model the noise introduced by scanning optics. In all the experiments, all the characters were required to maintain 10% of the total number of pixels in an ideal character to remain in the analysis datasets. This cutoff value was arrived upon after visual analysis and experimentation.

Moment features were calculated from the generated characters and were used to cluster the data into smaller homogeneous sets using Isodata clustering. The character stroke widths of similar looking characters within the same cluster partition of the synthetic generated characters were used to analyze and parametrize the DC and MDC edge spread degradation parameters. The values for edge spread degradation parameters DC and MDC that form good inter-cluster partition boundaries were noted. These values were used to divide and classify the dataset using a Bayesian classifier with the 10 fold cross validation approach. Different combinations of crisp and fuzzy testing and training of the Bayesian classifier were implemented to carry out the test point classification. The weighted percentage error of the cluster partitions was calculated and compared to the classification accuracy of an undivided dataset.

The scope of work in this thesis included analysis and experiments to analyze the questions:

1. Did the division of the dataset improve the accuracy of classifying the dataset?
2. Is MDC a better parameter to partition the dataset than DC?
3. What if the dataset was divided by a non-optimal DC and MDC values?
4. What is the maximum number of cluster partitions that a dataset should be divided into?
5. What is the error associated with estimating the wrong DC and MDC parameter for a character?
6. Does the use of a fuzzy approach of classification offer any improvement in performance over the crisp approach?

The answers to the above questions can be found in the discussion that follows. If the training dataset is unpartitioned, the classification accuracy is 94.08%. Tests verified that dividing the dataset by both DC and MDC did improve classification accuracy. Tables 3.1 and 3.2 indicate that classification accuracy as high as 98.08% was achieved by this new approach with 2 partitions and 98.93% with 3 partitions in comparison to 94.08% that we get without any data division and classification for the same dataset. The best classification accuracy was achieved for the 3 partition crisp training and fuzzy testing case when dividing the dataset by an MDC value, which was marginally better than division by DC.

It was established that the best classification accuracy is achieved when the dataset is divided by the MDC edge spread degradation parameter value that forms the perfect partition boundary for the 2 and 3 partition cases. This can be verified by looking at Figures 3.6 and 3.7. Marginally better classification accuracy was achieved by using MDC to divide the dataset over DC values for both these partition cases. These results agree with the visual observations that can be noted by looking at the cluster plots in Figure 3.7. This marginal improvement in classification accuracy becomes significant when we use this OCR engine to digitize a book that has thousands of pages and each page has thousands of characters. If the dataset was partitioned by the non-optimal DC or MDC value and the data was classified, the classification was still the same or better than when the data is unpartitioned. Hence, there is no disadvantage of using sub-optimal degradation parameter values to divide the dataset, as in the worst case scenario, there would be no improvement in classification accuracy but no decrease in accuracy either. In comparison, if we divide the dataset by the optimal DC and MDC values, a significant improvement in classification accuracy is possible.

To answer question 4, in this thesis, experiments were done with the data divided into different numbers of partitions upwards of 2 and it was concluded that the choice of up to 3 partitions is a valid choice. Beyond 3 partitions, the cluster partitions tend to mix with each other and we cannot get distinguished partitions. Also, the difficulty in fitting a degradation parameter boundary to divide the data to train and test as well as the impracticality of the implementation dictate the number of partitions to be 2 or 3.

The understanding required to reason questions 5 and 6 is the estimation that character parameter values may be incorrect, leading to incorrect grouping and subsequent misclassification of the test point. To overcome this problem, the 4 possible combinations of fuzzy and crisp training and testing approaches were implemented. The best classification results of 98.93% were achieved for the fuzzy testing and crisp training for a data set divided into 3 partitions by MDC shown in Tables 3.1 and 3.2. This better performance of the implementation can be justified by the fact that the fuzzy testing approach does not rigidly decide character class but makes provision for uncertainty. Every test point is considered as being in any of the possible partitions and all probabilities of being any character class is evaluated and a decision is made. Thus, the testing of each test point accounts for the best possible approximation, which in most cases does away with any bias or error in training in case it was present. This method is computationally intensive because of the many calculations. Considering the size of the dataset and the computational ability of the modern day computers, this calculation is not very demanding. The improvement in classification accuracy justifies this computer intensive operation.

4.1 Future Work

The experiments can be done on larger datasets having more datapoints and the datapoints can be extended beyond the ‘c’ and ‘e’ characters to accommodate other characters and numbers 0-9. We can also experiment with different resolution and font styles for the datasets. The Bayesian classifier used in this approach can be replaced by other classifiers, say for example a neural network, to analyze if that changes the classification accuracy. In this thesis, the 8 central moments of each character image were used as features. In future experiments, different features can be used for classification.

CHAPTER 5

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