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Development of a Feature Extraction Technique for Online Character Recognition System

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Abstract

Character recognition has been a popular research area for many years because of its various application potentials. Some of its application areas are postal automation, bank cheque processing, automatic data entry, signature verification and so on. Nevertheless, recognition of handwritten characters is a problem that is currently gathering a lot of attention. It has become a difficult problem because of the high variability and ambiguity in the character shapes written by individuals. A lot of researchers have proposed many approaches to solve this complex problem but none has been able to solve the problem completely in all settings. Some of the problems encountered by researchers include selection of efficient feature extraction method, long network training time, long recognition time and low recognition accuracy. This paper developed a feature extraction technique for online character recognition system using hybrid of geometrical and statistical features. Thus, through the integration of geometrical and statistical features, insights were gained into new character properties, since these types of features were considered to be complementary.

Keywords: Character recognition, Feature extraction, Geometrical Feature, Statistical Feature, Character.

1. Introduction

Character recognition is the process of applying pattern-matching methods to character shapes that has been read into a computer to determine which alpha-numeric character, punctuation marks, and symbols the shapes represent. The classes of recognition systems that are usually distinguished are online systems for which handwriting data are captured during the writing process (which makes available the information on the ordering of the strokes) and offline systems for which recognition takes place on a static image captured once the writing process is over (Anoop and Anil, 2004; Liu *et al.*, 2004; Mohamad and Zafar, 2004; Naser *et al.*, 2009; Pradeep *et al.*, 2011). The online methods have been shown to be superior to their offline counterpart in recognising handwriting characters due the temporal information available with the formal (Pradeep *et al.*, 2011). Handwriting recognition system can further be broken down into two categories: writer independent recognition system which recognizes wide range of possible writing styles and a writer dependent recognition system which recognizes writing styles only from specific users (Santosh and Nattee, 2009).

Online handwriting recognition today has special interest due to increased usage of the hand held devices. The incorporation of keyboard being difficult in the hand held devices demands for alternatives, and in this respect, online method of giving input with stylus is gaining quite popularity (Gupta *et al.*, 2007). Recognition of handwritten characters with respect to any language is difficult due to variability of writing styles, state of mood of individuals, multiple patterns to represent a single character, cursive representation of character and number of disconnected and multi-stroke characters (Shanthi and Duraiswamy, 2007). Current technology supporting pen-based input devices include: Digital Pen by Logitech, Smart Pad by Pocket PC, Digital Tablets by Wacom and Tablet PC by Compaq (Manuel and Joaquim, 2001). Although these systems with handwriting recognition capability are already widely available in the market, further improvements can be made on the recognition performances for these applications.

The challenges posed by the online handwritten character recognition systems are to increase the recognition accuracy and to reduce the recognition time (Rejean and Sargurl, 2000; Gupta *et. al*., 2007). Various approaches that have been used by many researchers to develop character recognition systems, these include; template matching approach, statistical approach, structural approach, neural networks approach and hybrid approach. Hybrid approach (combination of multiple classifiers) has become a very active area of research recently (Kittler and Roli, 2000; 2001). It has been demonstrated in a number of applications that using more than a single classifier in a recognition task can lead to a significant improvement of the system’s overall performance. Hence, hybrid approach seems to be a promising approach to improve the recognition rate and recognition accuracy of current handwriting recognition systems (Simon and Horst, 2004). However, Selection of a feature extraction method is probably the single most important factor in achieving high recognition performance in character recognition system (Pradeep, Srinivasan and Himavathi, 2011). No matter how sophisticated the classifiers and learning algorithms, poor feature extraction will always lead to poor system performance (Marc, Alexandre76 and Christian, 2001).

2. Research Methodology

Hundreds of features which are available in the literature can be categorized as follows: Global transformation and series expansion features, Statistical features and Geometrical and topological features. Many feature extraction techniques have been proposed in literature to improve overall recognition rate; however, most of the techniques used only one property of the handwritten character. This research focuses on developing a feature extraction technique that combined three characteristics (stroke information, contour pixels and zoning) of the handwritten character to create a global feature vector. Hence, in this research work, a hybrid feature extraction algorithm was developed to alleviate the problem of poor feature extraction algorithm of online character recognition system.

2.1 Development of the Proposed Hybrid Feature Extraction Algorithm

The most important aspect of handwriting character recognition scheme is the selection of good feature set which is reasonably invariant with respect to shape variation caused by various writing styles. Feature extraction is the process of extracting from the raw data the information which is the most relevant for classification purposes, in the sense of minimizing the within-class pattern variability while enhancing the between-class pattern variability (Naser *et al.*, 2009). Features are unique characteristics that can represent an image, i.e. a character in this case. Each character is represented as a feature vector, which becomes its identity. The goal of feature extraction is to extract a set of features, which maximizes the recognition rate with the least amount of elements. Many feature extraction techniques have been proposed to improve overall recognition rate; however, most of the techniques used only one property of the handwritten character. This research focuses on a feature extraction technique that combined three characteristics of the handwritten character to create a global feature vector. A hybrid feature extraction algorithm was developed using Geometrical and Statistical features as shown in Figure 2.10. Integration of Geometrical and Statistical features was used to highlight different character properties, since these types of features are considered to be complementary (Heute and Paquet, 1998; Cai and Liu, 1998).

2.1.1 Geometrical Features

Various global and local properties of characters can be represented by geometrical and topological features with high tolerance to distortions and style variations. This type of representation may also encode some knowledge about the structure of the object or may provide some knowledge as to what sort of components make up that object. The geometrical features used in this research work were the Stroke Information and Contour pixel of the characters.

2.1.1.1 Stroke Information

Stroke Information is a combination of local and global features, which are aimed to capture the geometrical and topological features of the characters and efficiently distinguish and identify the character from a small subset of characters. Stroke is storage of pen movements in online handwriting recognition. These movements appear at various positions on view point and joining these positions in first-come-first-serve basis shows the appearance of drawn text. A character may consist of single or multiple strokes. The list formed in data collection includes nodes, where each node includes two fields, namely, point and stroke number. Here, the point represents a coordinate of view point and stroke number represents identity and sequential order of stroke. Higher recognition performance would be possible if on-line recognition methods were able to address drawing motion vector (stroke) information (Nishimura and Timikawa, 2003). The feature sets consist of:

(i) Stroke Number

Stroke number helps in identifying similar points, gaps and crossings. The pen movement consists of three functions, namely, Pen-Down, Pen-Move and Pen-Up. When one presses, moves, lifts the pen up consecutively, and more than one point collected, the stroke number is incremented. Pen-Move function stores movements of pen on writing pad. An example of a digital pen for generating stroke information is as shown in figure 2.1. Figure 2.2 shows a typical example of how different stroke numbers are generated.

However, only stroke is not enough because most of the time different character may get the same no of strokes. Therefore, in this research, PEN-UP is used as a feature to check how well the character matches the standard one (i.e. the average for the same character in the database). This feature is calculated by using the average strokes of a specific character as an input using the membership function as in Equation 2.1:

$$\text{PEN-UP} = e^{|\text{average} - x|} \quad (2.1)$$

where x is the real strokes for the specific character.

(ii) Pressure of the Stroke

This is the pressure representing Pen Ups and Downs in a continuous manner. The use of pen pressure as a feature is used for the improvement of a basic performance of the writer- independent online character recognition. The value of the pen pressure exerted on the writing pad was also used as feature. Moreover, recognition performance could be raised using writing pressure information of on-line writer identification systems and on-line character recognition systems (Nishimura and Timikawa, 2003).

(iii) Number of Junctions and their Location

A black pixel is considered to be a junction if there are more than two black pixels in its 5 by 7 neighbourhood in the resolution of the character image. The number of junctions as well as their positions in terms of 35(5x7) quadrants are recorded. For example the character image of Figure 2.3 has 2 junctions in quadrants 2 and 17. Junctions lying within a pre-defined radial distance are merged into a single junction and the junctions associated with the headline are ignored.

(iv) Horizontal Projection Count

Horizontal Projection Count is represented as HPC(i) = $\sum_j F(i,j)$, where F(i,j) is a pixel value (1 for black background and 0 for white foreground) of a character image, and i and j denote row and column positions of a pixel, with the image's top left corner set to F(0,0). It is calculated by scanning the image row-wise and finding the sum of background pixels in each row (Figure 2.4). To take care of variations in character sizes, the horizontal projection count of a character image is represented by percentage instead of an absolute value and in this present work it is stored as a 4 component vector where the four components symbolize the percentage of rows with 1 pixel, 2 pixels, 3 pixels and more than 3 pixels. The components of this vector for the character image given in Figure 2.4 will be [50, 0, 10, 10], as there are 5 rows with 1 pixel; no rows with 2 pixels; 1 row with 3 pixels and 1 row with more than 3 pixels.

2.1.1.2 Contour Pixels

Correct extraction of the contour will produce more accurate features that will increase the chances of correctly classifying a given character or pattern. But the question that might arise is why first extract the contour of a pattern and then collect its features? Why not collect features directly from the pattern? One answer is, the contour pixels are generally a small subset of the total number of pixels representing a pattern. Therefore, the amount of computation is greatly reduced when feature extracting algorithms are run on the contour instead of the whole pattern. Because the contour shares a lot of features with the original pattern, but has fewer pixels, the feature extraction process becomes much more efficient when performed on the contour rather on the original pattern. Contour tracing is often a major contributor to the efficiency of the feature extraction process, which is an essential process in pattern recognition (Liu *et al.*, 2003; Liu *et al.*, 2004).

In order to extract the contour of the pattern, he following actions must be taken: every time a black pixel is encountered, turn left, and every time a white pixel is encountered, turn right, until the starting pixel is met again. All the black pixels traced out is the contour of the pattern. The contour tracing algorithm used in this research is based on the model developed by Yamaguchi *et al.* (2003). This is demonstrated in Figure 2.5 (Liu *et al.*, 2003; 2004).

Contour Tracing Algorithm (Yamaguchi *et al.*, 2003):

Input: An image *I* containing a connected component *P* of black pixels.

Output: A sequence B (b_1, b_2, . . . , b_k) of boundary pixels, that is, the outer contour.

Begin

Set B to be empty

From bottom to top and left to right scan the cells of I until a black pixel, S, of P is found

Insert S in B

Set the current pixel, P, to be the starting pixel, S

Turn left, that is, visit the left adjacent pixel of P

Update P, that is, set it to be the current pixel

While P not equal to S do

If the current pixel P is black

Insert P in B and turn left (visit the left adjacent pixel of P)

Update P, that is, set it to be the current pixel

Else

Turn right (visit the right adjacent pixel of P)

Update P, that is, set it to be the current pixel.

End

2.1.2 Statistical Features

Statistical features are derived from the statistical distribution of points. They provide high speed and low complexity and take care of style variations to some extent. They may also be used for reducing the dimension of the feature set. The statistical feature adopted in this research is 'Zoning'. Zone-based feature extraction method provides good result even when certain pre processing steps like filtering, smoothing and slant removing are not considered.

Image Centroid and zone-based (ICZ) distance metric feature extraction and Zone Centroid and zone-based (ZCZ) distance metric feature extraction algorithms were proposed by Vanajah and Rajashekararadhya in 2008 for the recognition of four popular Indian scripts (Kannada, Telugu, Tamil and Malayalam) numerals. In this research, hybrid of modified Image Centroid and zone-based (ICZ) distance metric feature extraction and modified Zone Centroid and zone-based (ZCZ) distance metric feature extraction methods was used. Modifications of the two algorithms are in terms of:

(i) Number of zones being used

(ii) Measurement of the distances from both the Image Centroid and Zone Centroid

(iii) The area of application.

2.1.2.1 The Zoning Algorithm

The most important aspect of handwriting recognition scheme is the selection of good feature set, which is reasonably invariant with respect to shape variations caused by various writing styles. The zoning method is used to compute the percentage of black pixel in each zone. The rectangle circumscribing the character is divided into several overlapping, or non-overlapping regions and the densities of black points within these regions are computed and used as features as shown in Figure 2.6. The major advantage of this approach stems from its robustness to small variation, ease of implementation and good recognition rate. Zone-based feature extraction method provides good result even when certain pre processing steps like filtering, smoothing and slant removing are not considered. The detailed description of Zoning Algorithm is given as follows:

The image (character) is further divided in to 'n' equal parts (Twenty five in this case) as shown in Figure 2.7. The character centroid (i.e. centre of gravity of the character) is computed and the average distance from the character centroid to each pixel present in the zone is computed. Similarly zone centroid is computed and average distance from the zone centroid to each pixel present in the zone is to be computed. This procedure will be repeated for all the zones/grids/boxes present in the character image. There could be some zones that are empty, and then the value of that particular zone image value in the feature vector is zero. Finally, 2 x 25 (i.e. Fifty in this case) such features were used to represent the character image feature. Algorithm 1 and Algorithm 2 were proposed by Vanajah and Rajashekararadhya in 2008 for the recognition of four popular Indian scripts (Kannada, Telugu, Tamil and Malayalam) numerals.

Algorithm 1: Image Centroid and Zone-based (ICZ) Distance Metric Feature Extraction System (Rajashekararadhya and Vanajah, 2008a)

Input: Pre processed numeral image

Output: Features for classification and recognition

Begins

Step 1: Divide the input image in to ''n'' equal zones

Step 2: Compute the input image centroid

Step 3: Compute the distance between the image centroid to each pixel present in the zone

Step 4: Repeat step 3 for the entire pixel present in the zone

Step 5: Compute average distance between these points

Step 6: Repeat this procedure sequentially for the entire zone

Step 7: Finally, ''n'' such features will be obtained for classification and recognition

Ends

Algorithm 2: Zone Centroid and Zone-based (ZCZ) Distance Metric Feature Extraction System (Rajashekararadhya and Vanajah, 2008b)

Input: Pre processed numeral image

Output: Features for classification and recognition

Begins

Step 1: Divide the input image in to n equal zones

Step 2: Compute the zone centroid

Step 3: Compute the distance between the zone centroid to each pixel present in the zone

Step 4: Repeat step 3 for the entire pixel present in the zone

Step 5: Compute average distance between these points

Step 6: Repeat this procedure sequentially for the entire zone

Step 7: Finally, n such features will be obtained for classification and recognition

Ends

2.1.2.2 Hybrid of the Modified Zoning Feature Extraction Algorithms

The following are the algorithms to show the working procedure of the modified hybrid zoning feature extraction methods:

Modified Algorithm 1: Image Centroid and Zone-based (ICZ) distance metric feature extraction algorithm.

Input: Pre processed character images

Output: Features for classification and recognition

Method Begins

Step 1: Divide the input image in to 25 equal zones as shown in Figure 2.7

Step 2: Compute the input image centroid as shown in Figure 2.8 using the formula:

Centre of gravity in the horizontal direction (x–axis) $= \sum_{n=0}^{n-1} x_i$, where n = width (2.2)

Centre of gravity in the vertical direction (y–axis) $= \sum_{m=0}^{m-1} y_i$, where m = height (2.3)

Step 3: Compute the distance between the image centroid to each pixel present in the zone as shown in Figure 2.8

Step 4: Repeat step 3 for the entire pixel present in the zone (five points in this case):

$d = d_1 + d_2 + d_3 + d_4 + d_5$ (2.4)

Step 5: Compute average distance between these points as:

Average Image Centroid Distance $D_I = d/5$ (2.5)

where d = total distance between the image centroid to the pixel measured at an of angle 20^0

Step 6: Repeat this procedure sequentially for the entire zone (25 zones).

Total Distance (P) $= D_{I1} + D_{I2} + D_{I3} + . . .+ D_{Im}$ (2.6)

Total Average Distance $j= \sum_{z=0}^{m-1} \frac{D_z}{m}$ (2.7)

where m = 25(total number of zones)

Step 7: Finally, 25 such features was obtained for classification and recognition.

Method Ends.

Modified Algorithm 2: Zone Centroid and Zone-based (ZCZ) distance metric feature extraction algorithm

Input: Pre processed character image

Output: Features for classification and recognition

Method Begins

Step 1: Divide the input image in to 25 equal zones as shown in Figure 2.7

Step 2: Compute the zone centroid for the entire pixel present in the zone as shown in Figure 2.9 using the formula:

Centre of gravity in the horizontal direction (x–axis) = $\sum_{n=0}^{n-1} x_i$, where n = width (2.8)

Centre of gravity in the vertical direction (y–axis) = $\sum_{m=0}^{m-1} y_i$, where m = height (2.9)

Step 3: Compute the distance between the zone centroid to each pixel present in the zone

Step 4: Repeat step 3 for the pixel present in a zone (5 points in this case)

Total Distance $D = D_1 + D_2 + D_3 + D_4 + D_5$ (2.10)

Step 5: Compute average distance between these points as:

Average distance $D_Z = D/5$ (2.11)

where D = distance between the zone centroid measured at angle 20^0 to the pixel in the zone

Step 6: Repeat this procedure sequentially for the entire 25 zones.

Total Distance (Q) = $D_{Z1} + D_{Z2} + D_{Z3} + . . + D_{Zm}$ (2.12)

Total Average Distance $k = \sum_{z=0}^{m-1} \frac{D_Z}{m}$ (2.13)

where m = 25(total number of zones)

Step 7: Finally, 25 such features were obtained for classification and recognition

Method Ends

The Hybrid Zoning Algorithm: Hybrid of Modified ICZ and Modified ZCZ

Input: Pre processed character image

Output: Features for Classification and Recognition

Method Begins

Step 1: Divide the input image into 25 equal zones

Step 2: Compute the input image centroid

Step 3: Compute the distance between the image centroid to each pixel present in the zone

Step 4: Repeat step 3 for the entire pixel present in the zone

Step 5: Compute average distance between these points

Step 6: Compute the zone centroid

Step 7: Compute the distance between the zone centroid to each pixel present in the zone.

Step 8: Repeat step 7 for the entire pixel present in the zone

Step 9: Compute average distance between these points

Step 10: Repeat the steps 3-9 sequentially for the entire zones

Step 11: Finally, 2xn (50) such features were obtained for classification and recognition.

Method Ends

2.2 The Developed Hybrid (Geom-Statistical) Feature Extraction Algorithm

Step 1: Get the stroke information of the input characters from the digitizer (G-pen 450)

These include:

(i) Pressure used in writing the strokes of the characters

(ii) Number (s) of strokes used in writing the characters

(iii) Number of junctions and the location in the written characters

(iv) The horizontal projection count of the character

Step 2: Apply Contour tracing algorithm to trace out the contour of the characters

Step 3: Run Hybrid Zoning algorithm on the contours of the characters

Step 4: Feed the outputs of the extracted features of the characters into the digitization stage in order to convert all the extracted features into digital forms

3. Conclusion and Future Work

In this medium, we have been able to develop an effective feature extraction technique for online character recognition system using hybrid of geometrical and statistical features. Precisely, a hybrid feature extraction was developed to alleviate the problem of poor feature extraction algorithm of online character recognition system. However, future and further research may be geared towards developing a hybrid of modified counter propagation and modified optical backpropagation neural network model for the aforementioned system. Also, the performance of the online character recognition system under consideration could be evaluated based on learning rates, image sizes and database sizes.

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Figure 2.1: The snapshot of Genius Pen (G-Pen 450) Digitizer for Character Acquisition

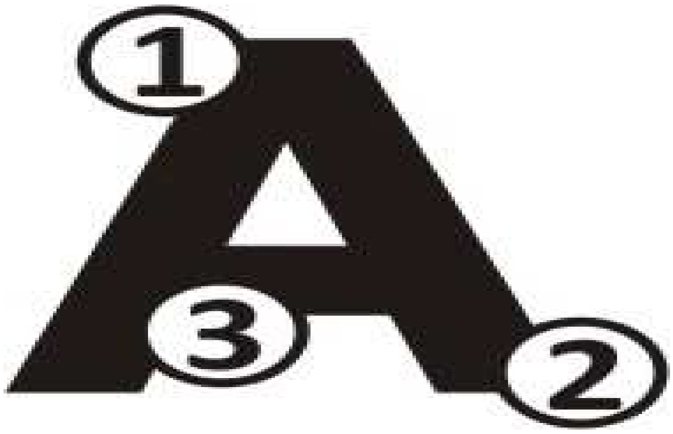
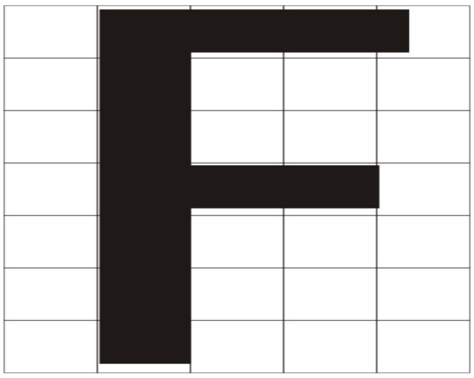


Figure 2.2: Writing character “A’’ with 3 Strokes



1	2	3	4	5
6	7	8	9	10
11	12	13	14	15
16	17	18	19	20
21	22	23	24	25
26	27	28	29	30
31	32	33	34	35

Figure 2.3: Division of character image into 35 quadrants

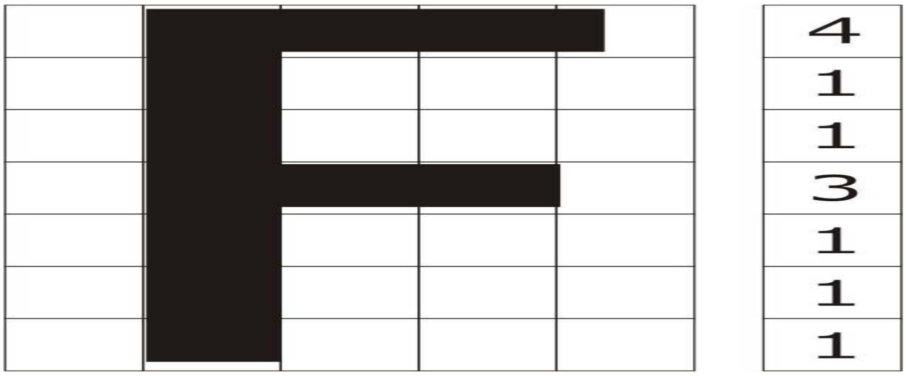


Figure 2.4: Horizontal Projection Count of character image ‘‘F’’

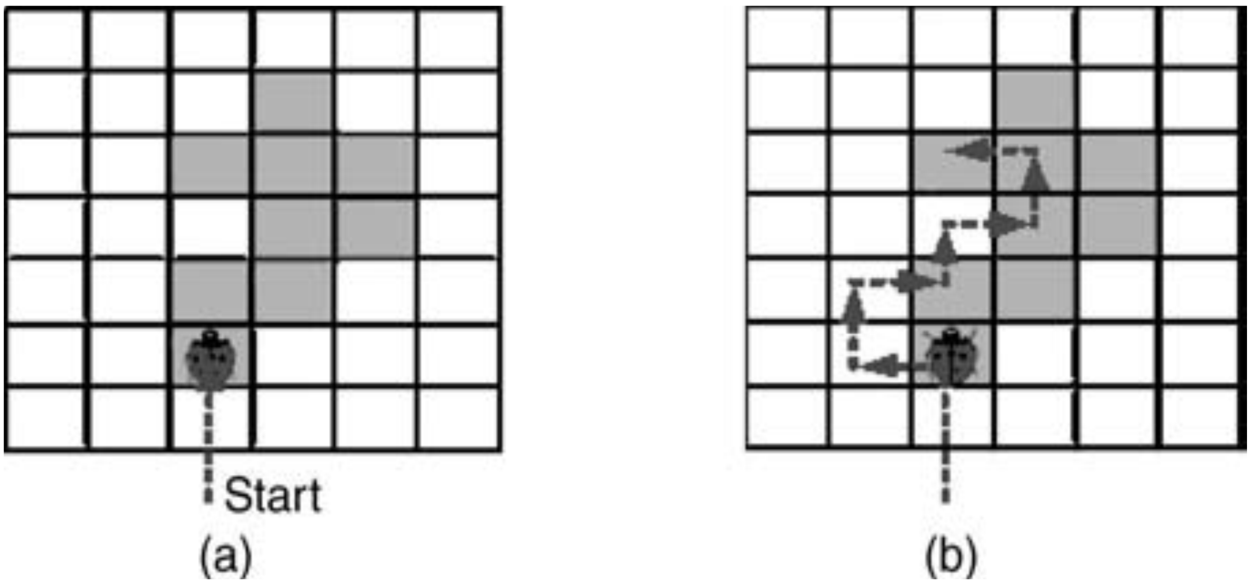


Figure 2.5: The Contour-tracing Algorithm (Yamaguchi *et al.*, 2003)

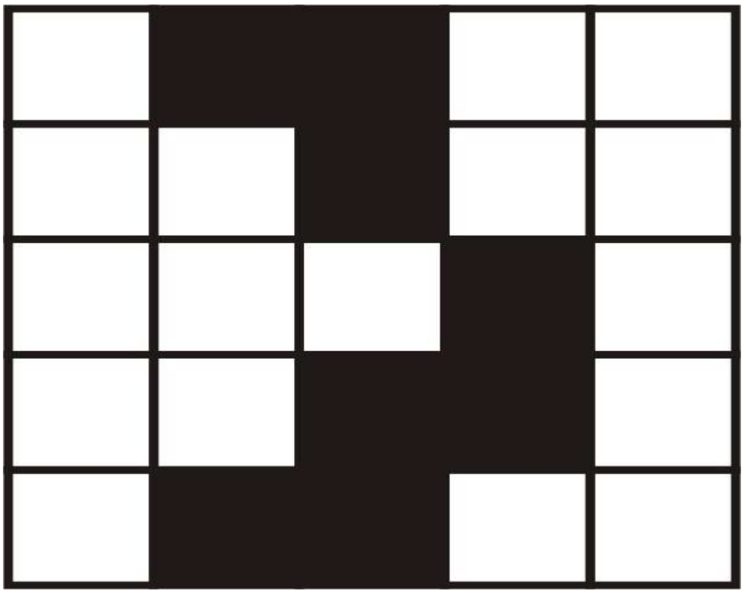


Figure 2.6: Feature Extraction using Zoning

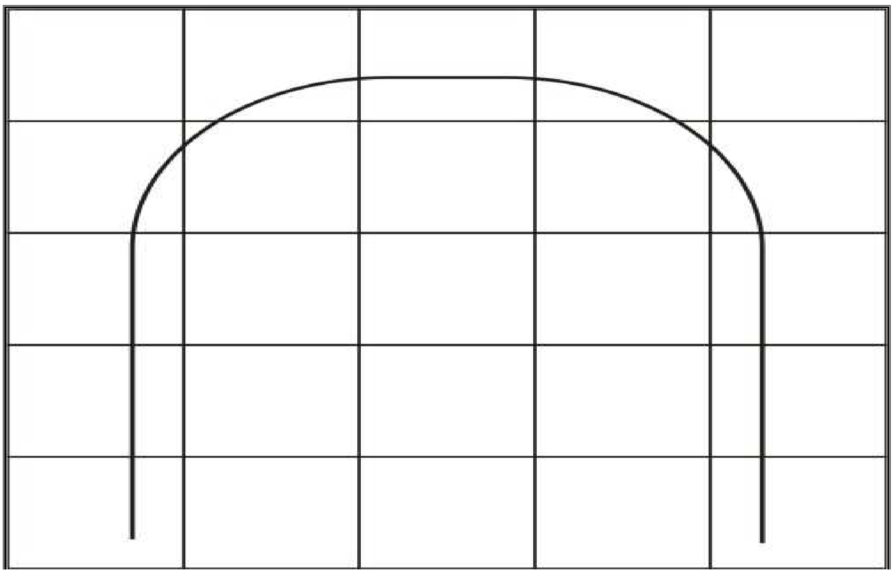


Figure 2.7: Character ‘‘n’’ in 5 by 5 (25 equal zones)

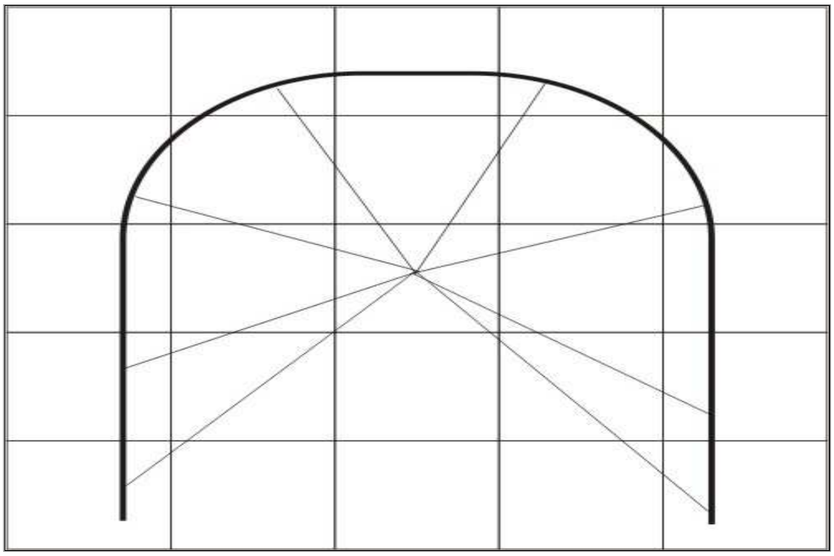


Figure 2.8: Image Centroid of character ''n'' in zoning

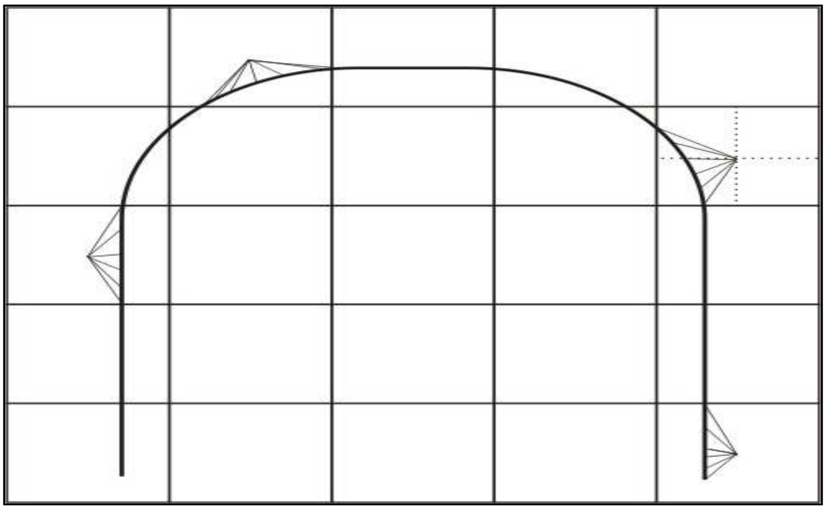


Figure 2.9: Zone Centroid of character ''n'' in zoning

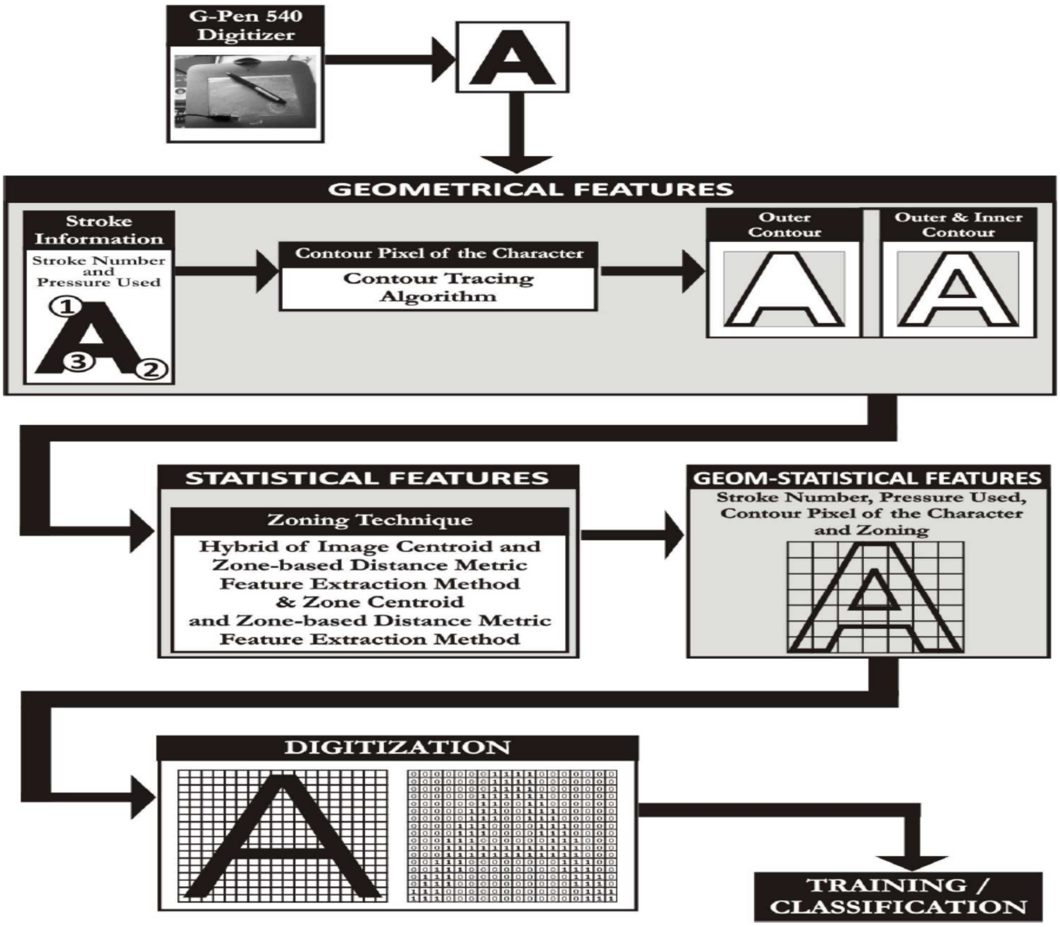


Figure 2.10: The Developed Hybrid Feature Extraction Model