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Feature Extraction Technique for Handwritten Character Recognition using Geometric-Based Artificial Neural Network

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Abstract—*Automatichandwritten characters recognition is a problem, which is currently gathering a lot of attention. The ability of an efficient processing small handwriting samples, such as those found on cheques and envelopes, is one of the significant driving forces behind this current research. This paper describes a geometry based technique for feature extraction which applies to the segmentation-based word recognition systems.In this methodology, an artificial neural network is trained to identify resemblance and patterns among different handwriting character dataset training samples and user-entered characters. The proposed system extracts the geometric features of character and thereby, forming a characterskeleton.The system generates feature vectors as outputs which are used to train a pattern recognition engine based on Neural Networks which makes the system benchmarked. We acquired an accuracy of 95.2% working on a set of 108 features. The Feature-Extraction methods described in this paper have performed well in classification when fed to the neural network, and pre-processing of the image using edge detection method and normalization technique are the ideal choice for degraded noisy images.*

Keywords—*ANN, Character skeleton, Direction feature, Geometry, Line type, Segment.*

I. INTRODUCTION

Handwriting recognition,been one of the most engaging and challenging research areas in the department of image processing and pattern recognition in the recent years [1] [3]. Several research works have been concentrating on new techniques and procedures that would reduce the processing time while providing remarkable recognition accuracy [5].

Online handwriting character recognition and offline handwriting character recognition of can be classified are the two classifications of the Handwriting recognition systems. In the off-line handwriting recognition, the handwritten charactersare usually captured optically by a scanner or any other image capturing device. Then the pre-processed received image is fed to the neural network for recognition. But, in the on-line handwriting recognition system, the two-dimensional coordinates of successive points are indicated as a function of time and the order of the strokes made by the writer are also available for the process of recognizing the characters raised by the writers. The on-line handwriting recognition methods have been shown to be superior to their off-line analog in recognizing handwritten characters due to the availability of temporal information with the former [2] [4]. As a result of this, the off-line handwriting recognition system continues to be an active area for research towards exploring the newer techniques that would enhance recognition process, performance and accuracy [9] [11].

The important initial step in any offline handwritten character recognition system is pre-processing of the image followed by image segmentation and feature extraction from the picture obtained. Pre-processing of the picture includessteps that are necessary to configure the input image into a form suitable for segmentation [8], which are further described the in section IIA of this paper. The commonly used feature extraction procedures are Deformable templates,Template matching, Unitary Image transforms,Fourier descriptors, Projection Histograms, Zoning, Geometric moment invariants,Graph Description, Zernike Moments, Spline curve approximation,Contour profiles, Gradient feature and Gabor features. Then the acquired features from the image are fed to the neural network for performing classification and recognition task. Pattern recognition functions widely use the neural network for performing tasks. In off-line handwritten character recognition system, the artificial neural networks have come out to be a quick and reliable tool for classification towards procuring high recognition accuracy and performance. Classification techniques includes: statistical methods based on Artificial Neural Networks(ANNs),Bayes decision rule, Kernel Methods including Support Vector Machines (SVM) [6] and multiple classifier combinations[7]. It is a challenging issue to develop practical handwritten character recognition (OCR) system which maintains high accuracy of recognition. The methodology employed in our work if of ANN for the implementation of Neural Networks. Artificial neural networks (or ANNs) are computational methods that perform multi-factorial analyses.

Motivated by networks of the biological neurons, an ANN model consists of layers of pure computing nodes that function as nonlinear summing devices. Weighted connection lines massively interconnect. The calibrated weights of the nodes are fed to the network during a training phase. Successful training result in artificial neural networks that can perform tasks like predicting an output value, classifying an object, recognizing a pattern in multi-factorial data,approximating a function, and completing a known pattern [10].

In Figure 1., each circular node pictures an artificial neuron and an arrow represents the connection directed from output of one neuron to input of another.

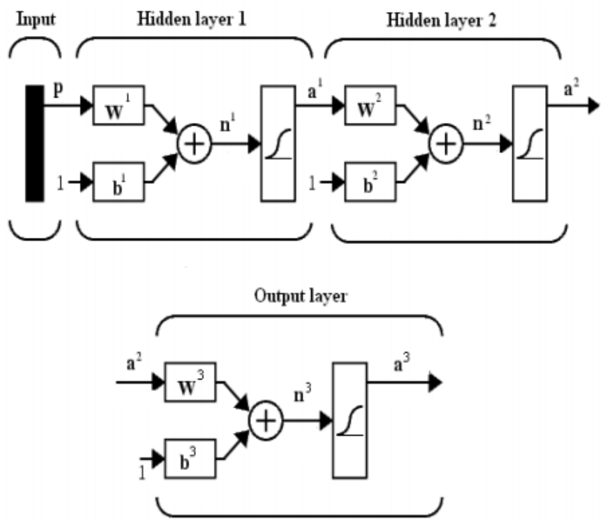

Figure 1. Diagram of a three-layer Artificial Neural Network.

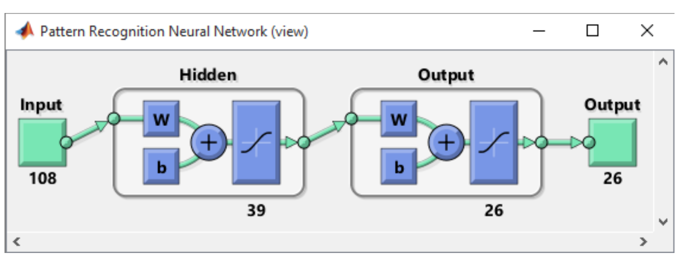

Figure 2. Neural Network implementation on MATLAB.

The reasons behind the use of artificial neural networks for segmentation purpose are as below:

1. The static segmentation method hasthe serious drawback that it is not capable of fixing the segmentation boundaries for the cases where inputs have size and inclination variations.

2. The static segmentation method also fails to fix segmentation boundaries for cases where there arediscrepancies in the inputs.

The solution for such situations can be given by ANNs, as these have the capability to learn shapes and that way recognize segmentation boundaries. Some of the segmentation methods relevant to practice are described in [12].For cursive writing, Cheng, Liu et. al [13] provides an elucidation of available segmentation methods. Use of artificial neural networks for segmentation has been mentioned by Blumenstein [14].

II. PROPOSED GEOMETRIC BASED AND NEURAL NETWORK CHARACTER RECOGNITION

The steps for implementation of ANN based character recognition is as shown in Figure 3. Its different stages are:

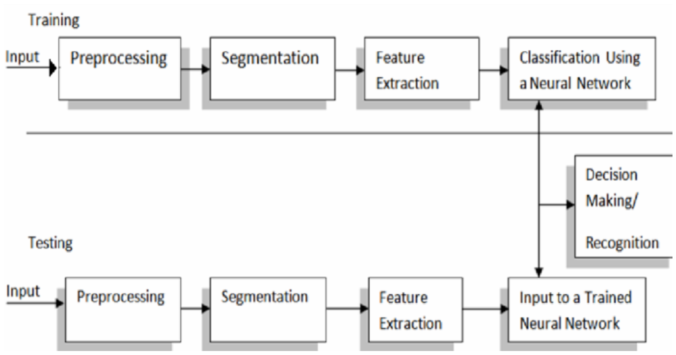

Figure 3. A generic character recognition system

- **Input:** Samples are read and provided to the system through a scanner.
- **Image Pre-processing:** The image pre-processing process converts the image into a form appropriate for subsequent processing and feature extraction, which is further described later in the section IIA.
- **Segmentation:** The most fundamental step in handwritten character recognition is to divide the input image into individual *glyphs*. This step extracts sentences from the text and eventually words and letters from penalties.
- **Feature extraction:** The process of extraction of features of a character forms a crucial module of the recognition process. Feature extraction captures the essential details of a character. [15]
- **Classification:** During the process of classification, class labels are assigned. Sub-Symbolic classifiers and Symbolic classifiers are the two categories of character classification. Artificial Neural Network (or ANN) character classification belongs to Sub-Symbolic classifier type.

A. IMAGE PRE-PROCESSING

Image pre-processing involves the following steps [16]:

- **Character Extraction from Scanned Document.**
- **Binarization:** The image is converted into the binary form to ease the computational load of the subsequent stages.
- **Background Noise Removal:** It involves the process noise removal using certain filtering operations and techniques.
- **Skeletonization:** Skeletonization is a process for minimizing foreground regions in a binary image to a skeletal residuum that mostly perpetuate the scope and connectivity of the original region while throwing away most of the foreground pixels.

The paper assumes that the input Image is available after undergoing all these processes.

B. UNIVERSE OF DISCOURSE

Itis the shortest matrix that fits the entire character skeleton [17]. It is selected because features extracted from the character image include thelocation of different line segments in the character image. So, every image of character should be independent of its image size.

Figure 4. (a) Original Image (b) Universe of Discourse [17]

C. ZONING

The universe of discourse is selected, then all the windows are equalized and the feature extraction is implemented on all the *window*. The character image is zoned into nine equal-sized *windows* and thenfeature extraction procedure was applied to individual zones obtained rather than using the process to whole the image, which helps in achieving greater efficiency for the process of feature extraction. This provides more information about the fine details of the character skeleton. Additionally, the positions of different line segments in a particular character frame become a quality if the zoning process is applied. This is since; a particular line segment of a character occurs in a particular zone in most of the cases. For instance, the horizontal line segment present in nature 'A' almost occurs inthe central region of the entire character area.

D. STARTERS, INTERSECTIONS AND MINOR STARTERS.

To extract distinct line segments from a particular zone, the entire character skeleton in that particular circumstances should be traversed. For this small purpose, certain pixels in the character regions are described as *starters*, *intersections*,and *minor starters*.

1. Starters

Starters are those pixels with one neighborin the character picture. Before the character traversal starts, all starters in the particular zone are found and then enlisted.

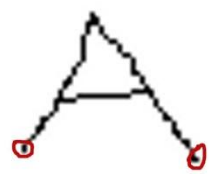

Figure 5. Starters are rounded [17]

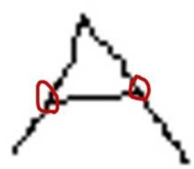

Figure 6. Intersections [17]

2. Intersections

The exact definition for intersections is somewhat more complex. Not so sufficient but a necessary criterion for a pixel to be an intersection is that it should possess more than one neighbor. A new property called *true neighbors* is defined for each pixel. Based on the quantity of true neighbors for a particular pixel, it is then classified as an intersection or not. For this, neighboring pixels are classified into two categories, one as*direct pixels* and the other as*diagonal pixels*. Direct pixels are all those who forms the neighborhood of the pixel under consideration both in horizontal and vertical directions. Whilediagonal pixels are the remaining pixels in the neighborhood which are in a diagonal direction to the pixel under consideration. Now to calculatethe number of true neighbors for the pixel under consideration, it has to be classified furtherfrom the number of neighbors it has in the character skeleton.

Pixels under consideration are classified as those with:

- ***Three neighbors***: If any of the right pixels is alongside to any of the diagonal pixels, then the pixel under contemplation cannot be an intersection, else if none of the neighboring pixels are adjacent to each other, then it is an intersection.
- ***Four neighbors***: If every direct pixel has an alongside a diagonal pixel or vice-versa, then the pixel which is under examination cannot be considered as an intersection.

- ***5 or more neighbors***: If the pixel under consideration has five or more neighbors, then it is always reckoned as an intersection.

Once all the intersections are recognized in the image, then they are enlisted.

3. Minor starters

These are found during the trajectory of traversal alongside the character skeleton. They are generated when the pixel which is under consideration have more than two neighbors. There are two locationswhere these are present:

Figure 7. Minor starters [17]

- *Intersections*: When the pixel under consideration is an intersection. The current line segment will terminate there, and all the neighbors that are unvisited are then enlisted in the minor starters list.

- *Non-intersections*: There are cases where the pixel under that is under consideration has more than two neighbors but still not an intersection. In such situations, the current direction of traversal is determined by using the position of the previous pixel. If any one of the unvisited pixels in the neighborhood is in that particulardirection, it is then contemplated as next pixel and all the other pixels are populated in minorstarters list.

When the algorithm proposed is implemented to the character image 'A,' in most of the cases, the minor starters found are illustrated in Figure 6.

III. CHARACTER RECOGNITION

A. Character Traversal

Character traversal procedure starts after zoning process is done on the input characterimage. Each zone is then separately subjected to the process of extracting line segments. For the same purpose, initially intersections and the starters in the region are found and then populated in the list. Minor starters are found along the trajectory of traversal. Algorithm is initialized by considering a starters list. Once all the starters are processed, the minor starters procured so are processed. All the line segments that are obtained during this process are stored, along with the positions of pixels in each of the line segments. Once all the pixels in the input character image are visited, the algorithm then stops.

B. DISTINGUISHING LINE SEGMENTS

After the process, when line segments have been extracted from the image, they are classified into any one of the types of lines as follows:

- Vertical line.
- Horizontal line.
- Left diagonal line.
- Right diagonal line.

For this classification, a *direction vector* is extracted from each of the line segments which will help in the process of determining each line type. For this process, a convention is required to define the position of the neighboring pixel concerning the center pixel of the 3x3 matrix which is under consideration. The naming convention is illustrated as follows.

4	5	6
3	*C*	7
2	1	8

In the above-given matrix, ’C’ represents the center pixel of the zone. The neighboring pixels are then numbered in a clockwise fashion starting from pixel just below the central pixel. To extract the direction vector from a line segment, the algorithm traverses through the entire pixels present in the line segments in the order in which they form the line segment. Though the above-described procedure identifies all line segments, one of itsdrawbacks is that, parts inthe shape of ‘V’ or any of its rotated variations will be detected as a single line segment. For instance, in the provided character image of ‘A’, the marked section is identified as a *single line segment*even though it is composed of two entirely different line segments.

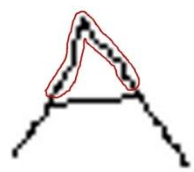

Figure 8. Image before application of direction rules

To prevent such type of errors, a new set of procedures is implemented. The segment illustrated in the diagram will be detected as one. A direction vector has been extracted, and a new process is applied to each of the direction vectors to find new line segments inside it. The direction vector is subjected to following procedures to find new line segments:

- If the previous trend was in 6 or 2 AND the next direction is in 8 or 4 OR.
- If the previous direction is in 8 or 4 AND the next direction is in 6 or 2 OR.
- If the direction of theline segment has been rotated to more than three types of direction OR.

The line segment marked in Figure 8 was obtained by applying the leadership rules explained above. Though this particular line segment is composed of two different line segments, it will be detected as a single line segment. But after applying the direction rules described above, the two line types will be distinguished. If a new line segment is detected, the direction vector is then broken down into two different direction vectors at that particular point. Now the following procedures are described for classifying each of the direction vectors:

- Line type is *right* diagonal if maximum occurring instruction type is 2 or 6.
- Line type is *vertical* if maximum occurring direction type is 1 or 5.
- Line type is *horizontal* if maximum occurring instruction type is 3 or 7.

If a condition arises when two line types are occurring forthe same number of times, then the sort, of course, detected first, among these two, is considered to be the kindof line of the segment.

IV. FEATURE EXTRACTION

Feature extraction can be described as a pre-processing step which removes disturbing variance from the dataset, so that the downstream classifiers or regression estimators can perform better [18].

After determining the line type of each segment, the feature vector is formedfrom this information. Each zone has a characteristics vector corresponding to it. Under the proposed algorithm, the length of the feature vector in every zone is 8. The contents of each zone feature vector are

- Count of vertical lines.

- Number of horizontal lines.
- Count of Left diagonal lines.
- Number of Right diagonal lines.
- Normalized Area of the Skeleton.
- Normalized Length of all vertical lines.
- Normalized Length of all horizontal lines.
- Normalized Length of all left diagonal lines.
- Normalized Length of all right diagonal lines.

The count of particular line types that are normalized uses

Value = 1 - ((count of lines/10) * 2)

Normalized length is determined by:

Length = (Total Count of Pixels in that line type)/ (Total Count of zone pixels)

The explained feature vector is extracted individually for each particular zone. So suppose, if there are N zones, then there will be 9N elements present in the feature vector for each particular zone. For the system proposed here, the original image was first zoned into nine individual zones by the division of the image matrix. Then the features were extracted from every zone. Again the division was done in the original image into 3 zones by dividing in the horizontal direction. Then features were extracted for each such region.

After the zonal feature extraction, certain features were extracted for the entire original image based on the regional properties of the image stated as follows:

- *Euler Number*: It is defined as the difference between the Count of Objects and Count of holes present in the character image. For instance, a well-drawn 'A' would have the Euler number as zero, since the count of objects present is 1 and count of holes presentare 2, while the character 'B' would have the Euler number as -1, due to the presence of two holes.
- *Regional Area*: It may be defined as the ratio of the count of pixels in the character skeleton to the total sum of pixels present in the character image.
- *Eccentricity*: It may be defined as the eccentricity of the smallest ellipse that can be fitted into the skeleton of the character image.

V. EXPERIMENTAL SETUP

This paper has been inspired by the work of Reference [19]. In many of the existing systems, recognition accuracy is heavily dependent on the quality of the input document. In the handwritten text, adjoining characters tend to be touched or overlapped. Thus, it is important to segment the given word correctly into its particular character components. However, the process of feature extraction based on local and global geometric features of the character skeleton has not been investigated on a substantial scale yet. Theconcepts as mentioned earlier are reflected in this algorithm as well. It extracts different line types that form a particular character and focuses on its positional features. The feature extraction technique explained is tested using a Neural Network which is trained with feature vectors obtained from the system proposed.We have considered parameters likeEpochs, the number of Hidden Layers and size of Hidden Layer. We have used Multilayer Feed Forward Network.Feedforward Neural Networks have been employed in the supervised learning of handwritten text as input. Backpropagation can be a future scope after evaluating the differentiable activation function or gradient of loss function of the given problem statement. The implementation used in the research is the simplest forms and efforts are made to optimize the result with minimum intervention in the original and traditional Artificial Neural Networks. In Pre-Processing, we have applied somein core algorithms for De-skewing, segmentation of characters and normalizing of characters. Thence, the test is used to find the accuracy of the respective Neural Network.

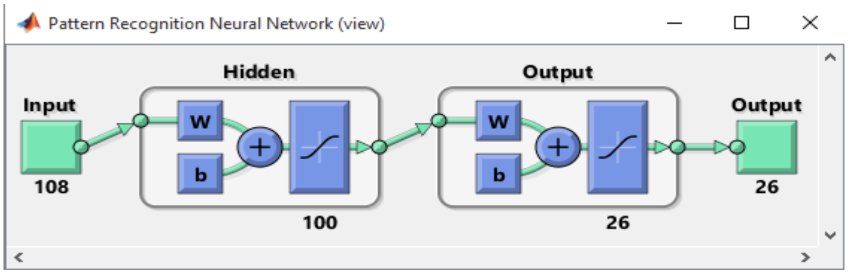

Figure 9. Simulation Result of the Artificial Neural Network used

Serial Number	Training Parameters	Values
1	Input nodes	108
2	Hidden nodes	100
3	Output nodes	26 (26 English alphabets)
4	Training goal achieved	0.018
5	Training algorithm:	Geometric Feature extraction with adaptive learning.
6	Training epochs	100000

Table 1. Network Parameters for the Neural Network.

The segmentation method used was efficient. The heuristic algorithm is based on rules which are deduced empirically, and there is no guarantee about their optimum results for different styles of writing. So their validation using neural network becomes essential.

VI. RESULT AND ANALYSIS

This paper has proposed a geometric feature extraction technique that is applied to the classification of characters for handwritten word recognition. The recognition system has been implemented using MATLAB R2013a (8.1.0.604). The scanned image is taken as dataset/ input. The structure of neural network includes an input layer with 108 input data, a hidden layer with 100 neurons and an output layer with 26 neurons. The method proposed is tested after training the Neural Network with a database of 650 images. The algorithm is tested with a testing set of 130 images, and only 6 of them were detected erroneously. The Feature-Extraction methods have performed well in classification when fed to the neural network, and pre-processing of the image using edge detection and normalization are the ideal choice for degraded noisy images.

The methodology proposed here has produced good results for images containing handwritten text which is written in a different size, different styles, and alignment with varying background color and texture. Themethod mentioned earlier has advantages as it uses nine features to train the neural network using character geometry and twelve features using the gradient technique. The geometric method of feature extraction is substantiated using many test images.

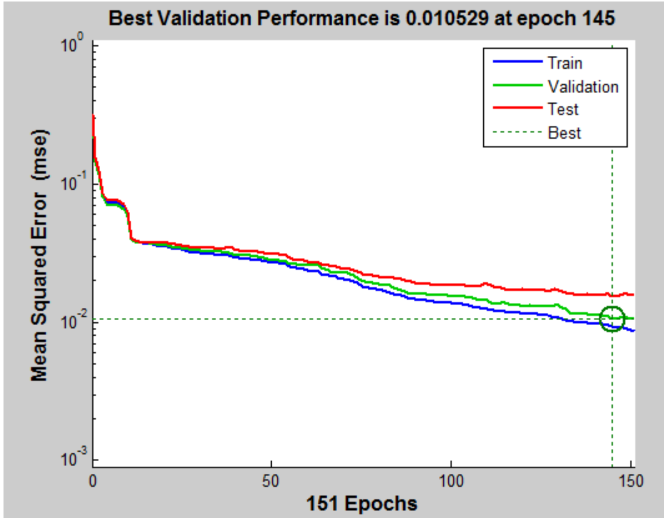

Figure 10. Performance Plot

In future, the method will be tried using a recurrent neural network so as to increase the performance and accuracy of the system. Also, more experiments may be conducted with additional benchmark datasets.

CONCLUSION

A simple off-line handwritten English alphabet character's recognition system using a new type of feature extraction, namely, geometric feature extraction is proposed. 108 features are chosen to build the Artificial Neural Network recognition system. To compare the recognition efficiency of the proposed geometric feature extraction, the artificial neural network recognition system is trained using the gradient technique and geometric feature extraction technique. From the test results, it is identified that the geometric feature extraction yields the highest recognition accuracy of 95.2 % for 108 features that are chosen. The geometric feature extraction is verified using many test images. Those mentioned above offline handwritten character recognition system using artificial neural networks (or ANNs) with better-quality credit rates will be highlyfitting for serval applications includingbank processing, postal/parcel address recognition, document reading as well asthe conversion of any handwritten document into a structural text form.

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