HANDWRITTEN ADDRESS DESTINATION RECOGNITION USING NEURAL NETWORKS

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Abstract
Most of the recent technological innovations are with some elements of artificial intelligence. This is replicated in this work to mimic the expertise of a post man in defining the destination of a posted mail. A system for destination address recognition of scanned addressed envelops image based on image processing and neural networks is developed. The system consists of three stages: preprocessing, neural network training and recognition. Neural network training is applied to find the aspects of address which are important for identification. The Neural network is used to create a number of 'state' database for the recognition of the destination of the address by using their weights. The system accepts hand-printed address block images as input. The main components of the system are image acquisition, image enhancement, address segmentation, feature extraction and character recognition. After extracting features of the address block on the envelope, the features extracted is used for the training and recognition of the destination address block. The system is trained with many samples to test the accuracy of the recognition of the neural network. The algorithm developed, is capable of distinguishing the city names in Nigeria on handwritten envelopes. In order to put the system to work in a real-time situation, the system architecture and related strategies are reported and experiments showed significant and promising results.

Keywords: Preprocessing, Neural Network, Image enhancement, Address segmentation and features extraction.

Study Background
Computer recognition of handwriting offers a new way of improving the human-computer interface. Since handwriting is one of the most familiar communication media, an automatic handwriting recognition system can offer a very easy and natural input method. Postal automation has always represented a main area of application for Image processing and Pattern Recognition techniques. Handwritten Character Recognition in mail processing has become an important part of mail delivery systems. The invention seeks to improve the effectiveness of sorting and delivery point processing in the post offices.

The handwritten character address block recognition is a challenging object recognition task due to the fact that address block varies in sizes and shapes. For a system to recognize the destination address block it requires relevant images for the successful training of the artificial neural network (Polikar, 2006). This required the techniques of machine and handwritten character recognition and low-level processing such as noise reduction, segmentation, features extraction and the actual recognition (Polikar, 2006).

Artificial Neural Network is used as a developed algorithm to train the network on how to recognize the destination address, which includes the city destination of the mail. The system requires that the handwritten character recognition must occur only on relevant portion of the envelope (Srihari&Kuebert, 1997).

The characters were prepared on a piece of blank paper envelop using varieties of writing pens and pencils. Purposeful sampling was used to obtain several samples of characters (each having different style) written by selected number of participants. These characters were captured using a scanning machine. The captured images were then preprocessed and used to generate input vectors for the backpropagation neural network for training. For the neural network training, separate character sets of some selected states (destinations) were also prepared using the same method as mentioned previously. Input vectors are generated and fed into the trained neural network for simulation. The program has the ability to capture the image on an envelope through careful filtering; analyze it, locate the destination address and then recognize the destination. The structure of the proposed neural network address recognition system is shown in Figure 1.

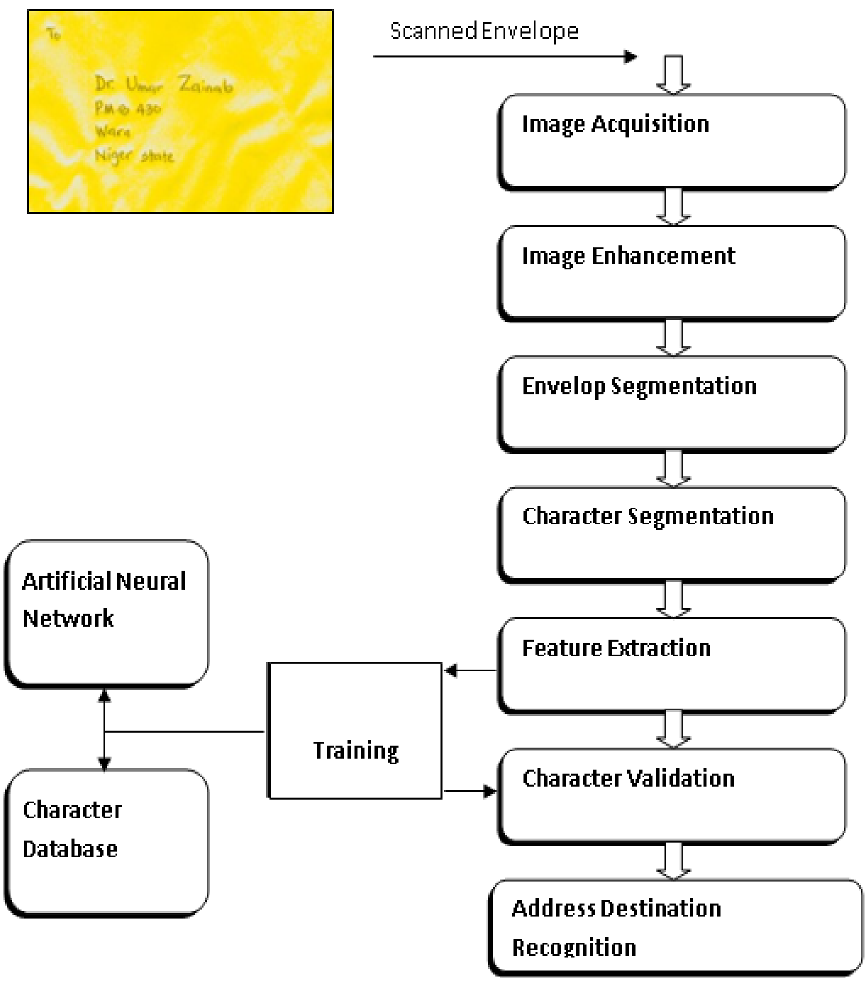

Figure 1: Simplified synopsis of the destination address recognition system

Statement of the problem

Today large volume mails increasingly demand faster, more reliable service and customized products. They require day-certain delivery, shipment and an electronic data interface. Mail-handling is a very laborious process and the knowledge level required for the sorting process is quite demanding. For important destinations like large cities direct bundles are formed, but for small villages mail is combined into bundles and dispatched to regional sorting centers for further onward sorting. The introduction of new postcode containing information which could be used for the entire mail-handling process calls for a more sophisticated approach (Sridhar, 1993). Thus, automatic reading is necessary for all the address fields necessary from the carrier to the final destination.

Research Objectives

The purpose of this paper was to develop simulation model for recognizing the destination of address block on envelop for mail-handling process. In achieving the primary objective, the following specific objectives were formulated:

(i) To develop algorithm for the character recognition system based on neural network;
(ii) To implement algorithm to a real world case study of the postal service system.

Literature Review

Handwritten Character Recognition has been a very active area of research. It is defined as a class of pattern recognition problem because of its characteristics of variance in sizes, shapes and invariant in its translation, scaling and orientation (Park, 1999). Also spaces amid characters are not linear and this makes it difficult to separate the spaces in between text. Consequently, the handwritten character address block recognition problem is a challenging object recognition task. Earlier work on this topic can be divided into four major areas, depending on whether the recognition units are characters, words, phrases, or longer bodies of text (Trier, Jain &Taxt, 1996).

Character recognition is a process of classifying pre-isolated character images within a given alphabet domain (Park, 1999). Fundamental reviews are found in Mori, Suen& Yamamoto (1992); Nagy (1992); Suen (1992) and Mantas (1986). It includes many subtopics which may be roughly divided into the following categories: feature extraction and selection, classification method, and combination of classifiers (Trier, Jain &Taxt, 1995). The handwritten character address block recognition problem is a challenging object recognition task. However, most researchers have adopted the classical pattern recognition approach in which feature extraction and classification preceded image pre-processing.

Feature Extraction and Selection

Feature extraction serves as important step in achieving good performance for a character recognition technique. The Extracted features must be invariant to the distortions and variations that can be expected in a specific application. The size of the feature set is also highly significant in order to avoid dimensionality problem (Trunk, 1979). The type of selected feature can determine the nature and output of the preprocessing steps and depends on the nature of the features to be extracted. That is, the decision whether to:

(i) use gray-scale versus binary image,
(ii) fill representation or contour,
(iii) thinned-skeletons versus full-stroke images.

Features are obtained from coefficients of various orthogonal decomposition methods by the representation properties of the image data (Trier, Jain & Taxt,1995). Feature extraction methods using topological features can generally reconstruct the image from the feature set. Types of reconstructive feature extraction methods includefourier descriptors (Lin & Hwang, 1987 and Granlund,1992), geometric moment invariants (Teh& Chin,1988; Abu-Mostafa& Psaltis,1984 and Hu, 1962), Zernike moments (Bailey & Srinath,1996) and Wavelet descriptors(Wunsch&Laine, 1995).

There are two important characteristics for describing feature sets. These are global versus local and symbolic versus reconstructive (Elliman& Lancaster, 1990). In global feature extraction, a feature vector is obtained from the coefficients of the expansion base function and this has detailed description at the same time. While in symbolic feature extractions, the feature measurements are usually transformed into symbolic representations of geometric primitives such as line segments, convexity, concavity, convex polygons, projections etc. Examples of the symbolic feature extractions are Gradient-based features (Srikantan, Lam &Srihari, 1996), projection histograms (Glauberman, 1956) and gradient structural concavity (Favata&Srikantan, 1996). Selection of the best features for a given application is a challenging task. However, solutions to the feature selection problem are proffered by several references. For instance, an algorithm which selects the best subset from a pre-existing feature set to maximize classification through various driving functions (Jain & Zongker,1997 andKira& Rendelland,1992) and an algorithm which automates feature generation using a random generator based on information and orthogonality measures (Gader&Khabou, 1996).

Classification Method

Major approaches to classical pattern classification method are statistical based, structural analysis, template matching, and neural network approaches (Duda, Hart, & Stork, 2000 and Schalkoff, 1992). Significant progress has been made in these classification methods but more work is required to match human performance.

Acccording to Favataand Srikantan (1996), multiresolution feature have been found to be more advantageous in classification than conventional methods that work with features at a single scale. A multi-resolution recognizer such as the Gradient Structural Concavity (GSC) uses symbolic multi-resolution features. The Gradient of the image contour captures the local shape of a character. The Gradient features are extended to Structural features by encoding the relationships between strokes. Concavity features capture the global shape of characters. Similarly, Thegenerative models based on iterative computation have also been proposed as a dynamic approach to handwritten character recognition (Revow, Williams and Hinton (1996). A Bayesian interpretation of the fitting process is adopted to yield a practical recognition algorithm (Duda, Hart, & Stork, 2000). This model has additional advantages such as description of style parameters, recognition based segmentation, small size of template, and pre-normalization compared to conventional classification algorithms. However, this approach still has problems such as computational complexity because of the burden of additional features and iterative fitting process.

Combination of Classifiers

Many recent research has shown improved performance using a combination of several different classification algorithms. Parallel classifier combination methods have been extensively studied, including adaptive voting principle(Suen, 1992 and Revow, Williams & Hinton 1996), Bayesian formalism(Lee & Srihari,1995 and Xu, Crzyzak&Suen, 1992), Dempster-Shafer theory(Lu & Yamaoka, 1994), neural network(Lee and Srihari, 1995).

Word Recognition

The handwritten word recognition algorithms usually take two inputs: pre-separated word image and a lexicon representing possible hypotheses for the word image. This is intended to assign a matching score to each lexicon entry or to select the best lexicon entry among the set. Various approaches for handwritten word recognition can be grouped into two major approaches. These include the analytical (model based) approach and the holistic approach.

Analytical Word Recognition

The analytical approach is designed to recognize the input word image as a series of units of a predefined model set known to the unit classifier. In this case unit segmentation forms part of the recognition process. Different model-based segmentation methods place different emphasis on the processes of segmentation and classification to reach the final recognition output (Simon, 1992).

Some of the most successful results have been achieved by segmentation driven techniques combined with matching algorithms of Dynamic Programming and Hidden Markov Models (HMM). In most cases a word image is segmented into sub-images called primitives without reference to the lexicon. Ideally a primitive is a character. Since perfect character segmentation is hard to achieve, in practice, an over-segmentation scheme is taken. A character segment can be a primitive or a union of primitives. All possible character segments are tried for matches with characters in the lexicon strings.

A recognizer that uses dynamic programming finds the prototype sequence which generates the best fit to the word image and yields the corresponding letter sequence as the recognized letter string or ranks the given lexicon with corresponding matching scores. Ordering primitives from left to right yields a partial ordering on the segments. A path though the partially ordered sequence of segments yields a segmentation driven by character recognition.

Holistic Word Recognition

Holistic approaches do not attempt to label parts of the image using sets of models (Farag, 1979). They extract holistic features from a word image and match the features directly against the entries of a lexicon. Holistic methods described in the literature used a variety of holistic features but they commonly include a variety of structural descriptions. Structural features are extracted from the image and they describe the geometric and topological characteristics.

These features are represented more robustly by a graph or a string of symbol codes, each code referring to a different feature or a combination of features. A location-coded string representation captures the locations in the image of each feature. The feature symbols and spatial relationships between features are represented by a graph representation that can show two dimensional relationships.

Some holistic classifiers have been developed for use in reduction of large lexicons and verification of recognition results obtained from other classifiers (Madvanath& Govindaraju,1995).

Word Recognition Combination

To optimize system performance, multiple word recognizer combination (Madvanath& Govindaraju, 1995) and control strategies (Madvanath, et al.1996) have been proposed. In Madvanath, et al. (1996), multiple recognizers are connected in a serial path. A decision making strategy is applied at each intermediate connection on this path. At each stage, a recognition result can be produced if the recognition results are of a high enough quality. This control strategy achieves a better performance than that obtained by using a single recognizer only.

Phrase Recognition

Some character recognition and word recognition studies have been extended to text and phrase recognition in applications of postal address interpretation (Cohen, Hull &Srihari, (1994), bank check processing (Simon, Barat &Gorski, 1994) and tax form processing (Srihari et al., 1996). Previous research efforts related to handwritten phrase/text recognition problems most often assumes that words are already isolated or can be perfectly isolated.

The study of handwritten phrase recognition algorithms has been lacking compared to recognition of isolated units. Generally the scheme of phrase recognition systems follows the processing flow consisting of these steps: word segmentation, word recognition and post-processing. Separated word images are sent to a word recognizer and contextual information and linguistic constraints are used in post-processing to complete the phrase selection process, assuming that word images are perfectly isolated.

Postal Automation

The main function required in postal automation, involving Computer Vision is definitely address reading and interpretation. Nevertheless, due to the inherent 2D nature of the problem its computer implementation is strongly based on basic technologies as image processing and pattern recognition. At present, the most challenging tasks, performed by such Vision technologies in postal automation, are handwiting cursive recognition, flats handling and reading, grey level and colour image processing, improved man-machine interaction, and robotic material handling.

Concept of Artificial Neural Network

Artificial Neural Networks has been widely used for pattern classification in a variety of fields including character recognition, speech recognition, image recognition and signal processing. The idea of neural networks is derive from the way neurons interact and how it functions in the natural animal brain, especially

Humans (Haykin,1998 and Bishop, 1995). Neural network have ability to learn how to solve problems based on the data given by training. Multilayer perceptron which can be trained based on back propagation is adopted in this research work.

The model consists of the following elements:

- Processing units (artificial neurons)
- Weighted interconnection (neurons connections)
- Activation rule to propagate signals through network
- Learning rule to specify how weights are adjusted

Neural networks is an information processing system composed of interconnected network of artificial neurons. Each neuron is linked to certain of its neighbors with varying weights.

The neural network is trained to learn from experience to solve different problems. In other words, neural network is a cellular system that can acquire, store and utilize experiential knowledge. Figure 2.Neural network training.The principal advantages of backpropagation are simplicity and reasonable training speed. It is well suited to Pattern recognition problem. The back-propagation algorithm (Cristea,1999)is given inFigure

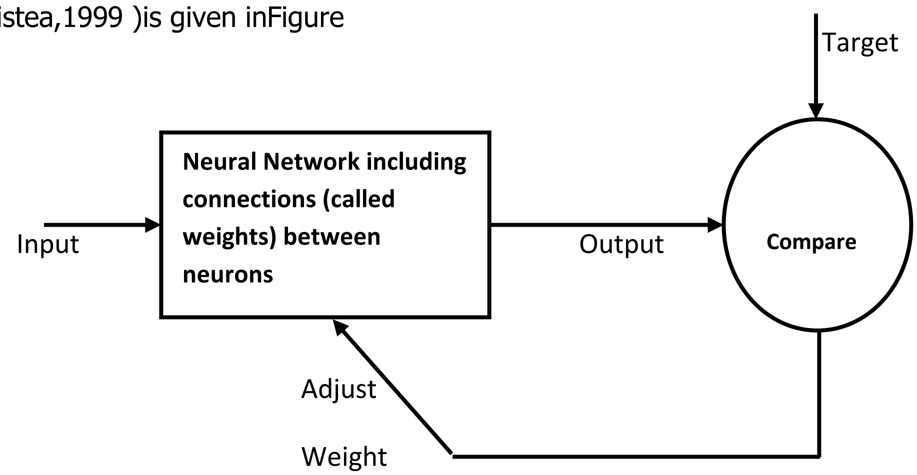

Figure 2: The back-propagation algorithm

The training is based on a gradient descent in error space, wherethe error is defined as:

$$E = \sum_{P} E_P \qquad (1)$$

Back-propagation algorithm:

1. Initialize all synaptic weights w to small random values.
2. Present an input from the class of learning examples (input/output pattern) and calculate the actual outputs.
3. Specify the desired outputs and evaluate the local error " for all layers.
4. Adjust the synaptic weights to minimize ".
5. Present another input pattern corresponding to the next learning example (repeat step 2).

whereE_P is the error of each input pattern and

$$E = \frac{1}{2}\sum_i (T\arg et_i - Input_i)^2 \qquad (2)$$

We can adjust the weights in step 4 corresponding to the gradient of error:

$$\Delta w = -\eta \nabla E \qquad (3)$$

whereη is a constant scaling factor defining the step-size of training. Once the neural network is trained, it can classify any incoming feature vectors effectively and accurately.

The ANN models have been developed in various disciplines to recognize patterns or approximate functions from complicated data and to make. The handwritten character recognition is complex and non-linear process, thus the neural network approach is appropriate for handwritten character recognition. Neural networks are composed of simple elements operating in parallel (Figure 3) The neuron model shown in Figure 4 is the one that widely used in artificial neural networks with some minor modifications on it.

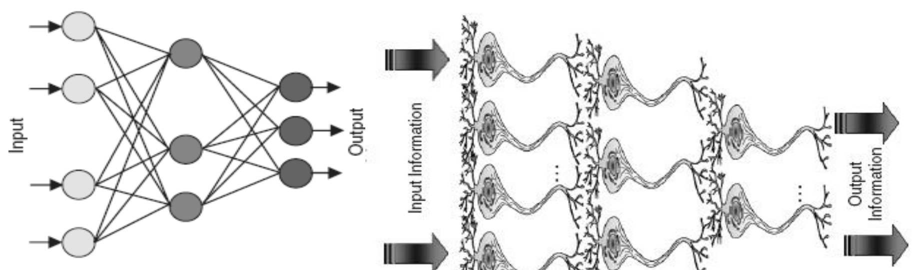

Figure 3: Neural networks

The artificial neuron given in this figure has N input, denoted as x_1, x_2,…x_N. Each line connecting these inputs to the neuron is assigned a weight, which is denoted as w_1,w_2,….,w_N respectively.

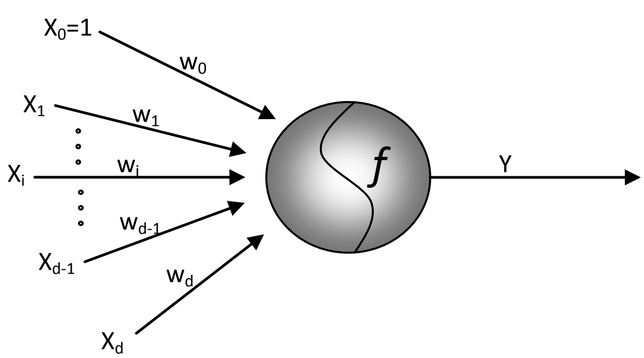

Figure 4: Artificial neuron

Methodology

Image preprocessing
Image preprocessing is defined as the extraction of appropriate invariant features that are then used for recognition system by the classifier system. Characters are preprocessed to improve performance of the pattern recognition system. This involves algorithm like scaling the characters to a standard size, reduction of noise in the character preprocessing algorithm may also be employed to make the character images font–independent

Image acquisition
The approach used for the envelope acquisition was to scan the image horizontally looking for repeating contrast on the scale of the pixel. The particular value is determined by the resolution of the scanner. 100dppi resolution was chosen for the scanned image. Some amount of skew is usually introduced when a document is scanned. Before any further processing it is necessary to ensure that the document is aligned properly. There can be skew associated with entire document or with individual characters. In both cases, it needs to be corrected before further processing. The nearest neighborhood clustering method is used to determine the skew.

Image enhancement
In image analysis and enhancement problem it is very essential to identify the object of interest from the rest. The handwritten address on the envelope is removed from the background pixel. The segmented uses black as background image and the foreground is white Image segmentation tends to partition the scanned into two exclusive and collectively.

Features extraction
A feature is a component representation of the information content in data. At each feature location (peak) a feature vector is extracted which describes the local neighbourhood surrounding the peak. Sobel gradient operator was applied on the pre-processed image on the characters on the envelope. The features of the characters extracted are fed into the neural network for its training.

Training process
The original document is scanned into the computer and saved as an image. The code breaks the image into sub-images, each containing a single character. The sub-images are then translated from an image format into a binary format, where each 0 and 1 represents an individual pixel of the sub-image. The binary data is then fed into a neural network that has been trained to make the association between the character image data and a numeric value that corresponds to the character. The output from the neural network is then translated into ASCII text and saved as a file as illustrated in Figure 5.

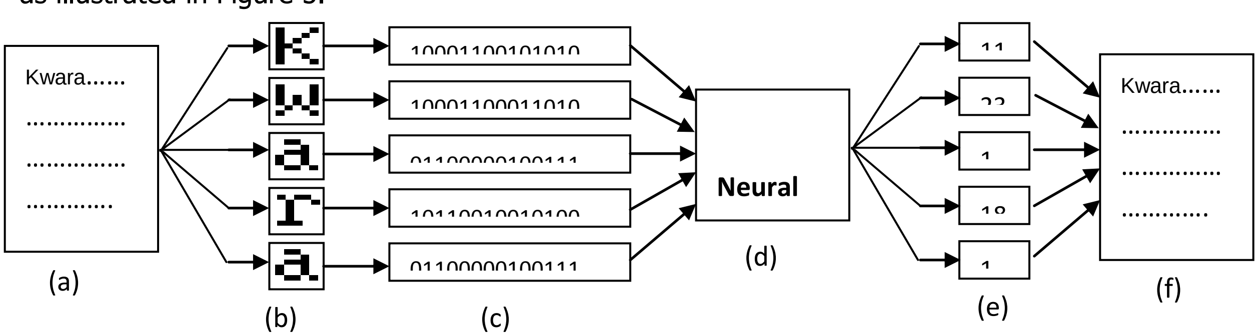

Figure 5: Training process

(a) represents image of a scanned envelop.
(b) represents sub-images of individual destination of the address from envelop.
(c) represents Binary representation of the sub-images obtained by morphological binarization techniques. i.e 0 is white and 1 is black.
(d) represents the supervised neural network which is trained to recognize images of the characters.
(e) represents the neural network output i.e. numeric values corresponding to the recognized characters.
(f) represents file containing the text of the scanned document.

Analytic techniques
It is well-known that reasonable models for human vision system are basically computational. In this research we develop theory for automated understanding of observed images and recognition of interesting objects in the images. Using ideas from Young, Gerbrandsand Van Vliet (1998) we seek to: derive efficient representations of arbitrary scenes; derive probabilistic models for these representations and write algorithms for statistical inferences.

Segmentation
The basic idea of image segmentation is to group individual pixels together into regions if they are similar. Similar can mean they are the same intensity (shade of gray), form a texture, line up in a row, create a shape, etc. The techniques that are used to find the objects of interest are usually referred to as *segmentation techniques.* In the preprocessing stage it is essential that we can distinguish between the objects of interest and the background i.e segmenting the foreground from background. In this project we will employ two of the most common techniques i.e. *thresholding* and *edge finding. Also* we will present techniques for improving the quality of the segmentation result.

Thresholding
In this technique we consider a chosen parameter $\theta\cdot$called the *brightness threshold* which is applied to the image $a[m,n]$ as follows:
For dark objects on a light background we would use:

If $a[m,n] < a[m,n] = object = 1$

Else $a[m,n] = background = 0$ (4)

Thus, this algorithm assumes that we are interested in dark objects on a light background.

The computed global image threshold is achieved using Otsu's method with Matlab in the course of this research as follows:

Image_thresh = graythresh(image) (5)

The graythresh function chooses the threshold to minimize the intraclass variance of the black and white pixels. Figure 6 shows an example of their text extraction process. We see that there is an intimate relationship between edges and regions.

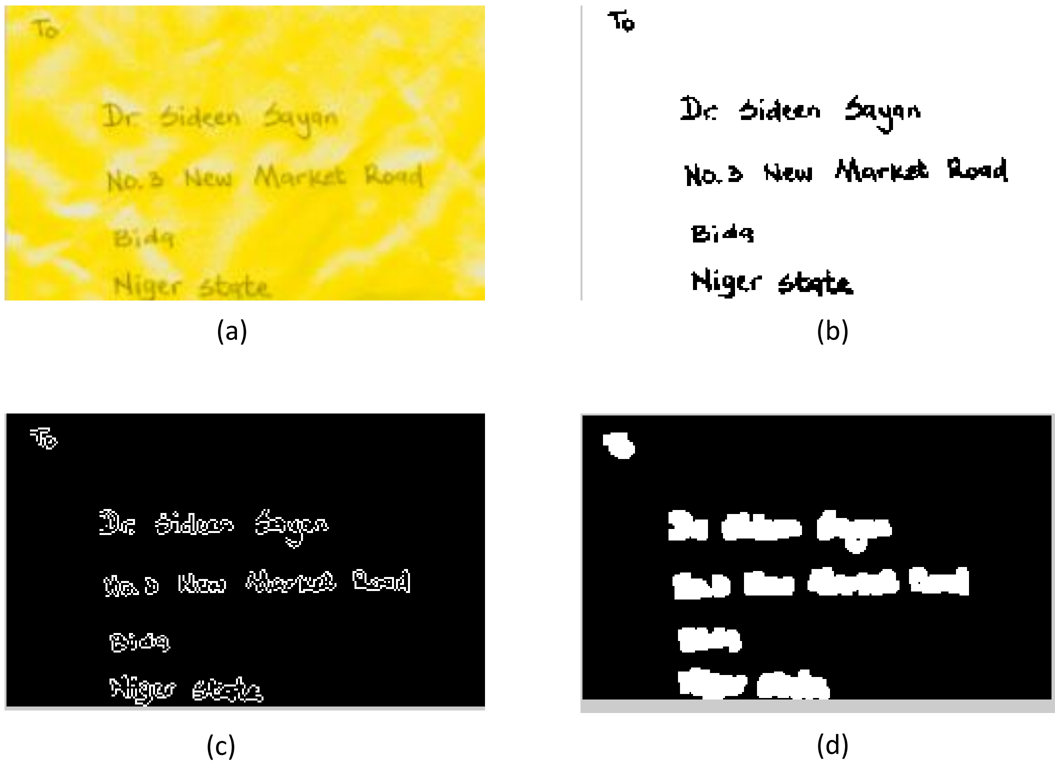

Figure 6: Intermediate stages of processing (a) original address envelop; (b) image segmentation; (c) after edge finding; (d) after binarization and dilation.

The group of pixel, the handwritten address on the envelope is removed from the background pixel. The segmentation uses black as foreground image and the background is white. The image binarization converts the scanned characters on the envelope to its binary form 0's and 1's.

Edge finding

After the thresholding that produces a segmentation that yields all the pixels that belong to the objects of interest in the image. The next step is to find those pixels that belong to the borders of the objects. Techniques that are directed to this goal are termed *edge finding techniques*. There are many techniques available for image *edge finding*, and they vary in complexity, power, and area of application. The Sobel method is employed and this finds edges using the Sobel approximation to the derivative. It returns edges at those points where the gradient of Image is maximum. The sobel gradient filters are specified as follows (Young, Gerbrands& Van Vliet,1998):

$$[I_x] = \frac{1}{4}\begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} = \frac{1}{4}\begin{bmatrix} 1 \\ 2 \\ -1 \end{bmatrix} \bullet \begin{bmatrix} 1 & 0 & -1 \end{bmatrix} \qquad (6)$$

$$[I_y] = \frac{1}{4}\begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} = \frac{1}{4}\begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} \bullet \begin{bmatrix} 1 & 2 & 1 \end{bmatrix}$$

Features extraction

A feature is a component representation of the information content in data. At each feature locationx, we would like to extract a feature vector which describes the local neighbourhood surrounding x. Sobel gradient operator was applied on the pre-processed image on the characters on the envelope, where features of the characters are extracted to serve as input into the neural network for its training.

Classify Character

Once segmented characters are represented by feature vectors, a host of pattern classification techniques can be applied. We have used the training method described earlier chapter 2 that produces multi-layer feed-forward back-propagation Neural Network with performance equal or better than character recognition. This is achieved with a single three_layer network by making fundamental changes in the network optimization strategy as discussed earlier2. A network of size 128x128x26 was used to classify the alphabetic character.

Training and Simulation of Neural Networks for Recognition

Neural networks have been trained to perform complex functions in various fields of application including pattern recognition, identification, classification, speech, vision and control systems. In this paper, there is one neural network for subimages of individual letter from word document. The feature vectors are calculated for the sub-image on the address envelop. These feature vectors are used as inputs to train the each destination networks. The Algorithm is shown under results.

Analyzing the Result

The percentage of recognition is calculated as

Percentage of recognition = $$\frac{Numberof\ recognised\ envelope}{Total\ Number\ of\ test\ data} \times 100 \qquad (7)$$

Percentage of unrecognized envelop is calculated as

Percentage of recognition = $$\frac{Numberof\ unrecognised\ envelope}{Total\ Number\ of\ test\ data} \times 100 \qquad (8)$$

The ratio of the percentage recognized envelope and unrecognized envelope is taken to see how effective the developed system is.

The implementation of this project work has been done mostly using Matlab version 7.1 and the accompanying Image Processing Toolbox. MATLAB is a high level language for technical computing; it is a programming system with many mathematical methods implemented. It also has many toolboxes. The system supports procedural programming and has some object-oriented programming capabilities. A basic data structure is the array. MATLAB has many functions for processing arrays that are useful. Multidimensional arrays are supported. A 1-D array may be referred to as a vector. A 2-D array is referred to as a matrix. The terms array and matrix are sometimes used interchangeably. There are built in functions for performing standard matrix operations as described in linear algebra topics. An image would be a 2-D array or matrix in this notation. The matrix operations are often the most efficient ways to implement algorithms since they have been optimized. The system has another data structure called cell arrays where the elements are cells. A cell can hold other arrays of any size and type. It is a flexible and useful data structure. MATLAB has:

(i) Wide variety of modeling and pre-processing tools already available
(ii) Flexibility to create custom applications, as well as custom pre-processing
(iii) Open architecture, allows 4^{th} party participation
(iv) Numerous standardization approaches
(v) Users in many different disciplines (helpful when "linking" analytical and dynamic systems)

Results and Discussion

Developed Algorithm for Implementation

1. Form network according to the specified topology parameters
2. Initialize weights with random values within the specified ±weight_bias value
3. load trainer set files (both input image and desired output text)
4. analyze input image and map all detected symbols into linear arrays
5. read desired output text from file and convert each character to a binary Unicode value to store separately
6. for each character :
7. calculate the output of the feed forward network
8. compare with the desired output corresponding to the symbol and compute error
9. back propagate error across each link to adjust the weights
10. move to the next character and repeat step 6 until all characters are visited
11. compute the average error of all characters
12. repeat steps 6 and 8 until the specified number of epochs
13. Is error threshold reached? If so abort iteration
14. If not continue iteration

Testing Algorithm

- load image file
- analyze image for character lines
- for each character line detect consecutive character symbols
- analyze and process symbol image to map into an input vector
- feed input vector to network and compute output
- convert the Unicode binary output to the corresponding character and render to a text box

Input data

- This consists of images of grey levels of size 2000 x 2000 pixels or more. Visual criteria and the information content of such mail pieces are briefly summarized in the following
- The address block to look for is composed of dark ink characters on a lighter background (either a white label or the gray colour of the envelope). Samples of processed envelopes are shown in Figure 7.

(a) (b)

(c) (d)

Figure 7: Samples of processed envelope

The group of pixel, the handwritten address on the envelope is removed from the background pixel. The segmentation uses black as foreground image and the background is white. The image binarization converts the scanned characters on the envelope to its binary form 0's and 1's.

- The format and size of the characters is arbitrary and cannot be established a-priori, especially for handwritten addresses. It is anyway smaller than other printed material present on the flat.
- The address lines do not have a fixed known direction, although typewritten text is mostly horizontal or vertical (unless for the free labels inserted into plastic envelopes).

Neural Network Parameters used in the Experiment

Number of hidden neurons = 1500
Number of epoch = 1514
Training algorithm = 'trainscg'
Transfer function used in hidden layer = 'tansig'
Transfer function used in output layer = 'logsig'

Table 1: Result analysis

Input data	Test Data	No of hidden layer	Recognized Envelope	% of Recognised envelope	Unrecognised Envelope	% of Recognised envelope
Kwara	I0	5	8	80	2	20
Lagos	30	6	27	90	3	10
Niger	15	7	14	93.33	1	6.67
Ogun	10	6	9	90	1	10
Oyo	10	5	8	80	2	20
Ekiti	15	3	10	66.67	5	33.33
Ondo	20	3	15	75	5	25
Gombe	10	8	10	100	0	0
Borno	20	5	17	85	3	15
Enugu	5	3	3	60	2	40
Benue	5	5	4	80	1	20
Kano	5	8	5	100	0	0
Jigawa	5	3	3	60	2	40
Bauchi	10	5	9	90	1	10

Result Evaluations

From the above result it is observed that the number of hidden neuron affects the recognition capability of the artificial neural network. The number of epoch also affects the recognition of the neural network. Therefore, to train a particular pattern large number of training data is required. A sample of the interface is shown in Figure 8.

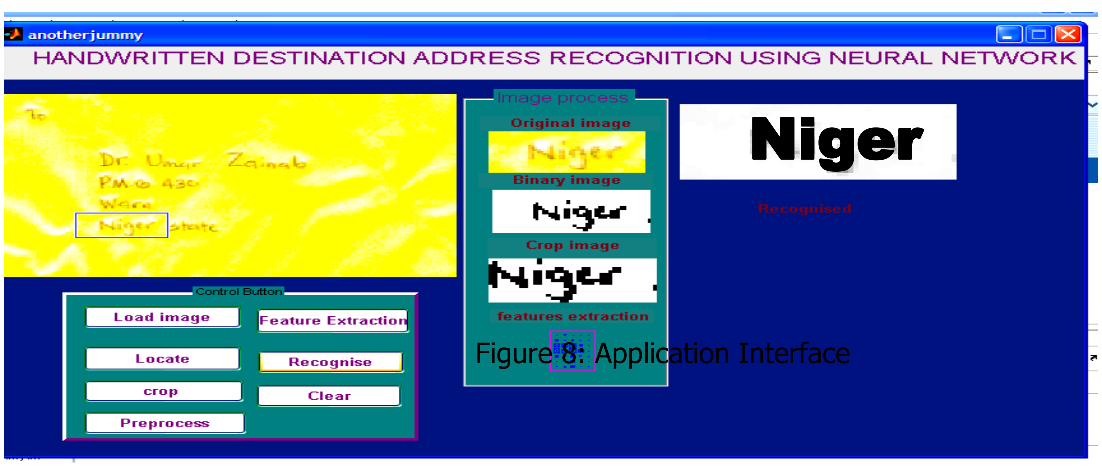

Figure 8: Application Interface

Conclusion

Using artificial Neural Network in character recognition is biological motivated and seems like an interesting approach not only to character recognition, but machine recognition in general as evidenced from the implementable algorithm discussed in this paper. Further research should be carried out on handwritten recognition to be able to recognized phrase recognition irrespective of whether the set of training data uses capital letter or small letters.

Recommendation

Further studies should be carried on in the aspect of handwritten word or phrase recognition system in order to increase the computer vision in the aspect of artificial Neural Network.

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