Recognition of Handwritten Arabic (Indian) Numerals Using Freeman’s Chain Codes and Abductive Network Classifiers

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Abstract—Accurate automatic recognition of handwritten Arabic numerals has several important applications, e.g. in banking transactions, automation of postal services, and other data entry related applications. A number of modelling and machine learning techniques have been used for handwritten Arabic numerals recognition, including Neural Network, Support Vector Machine, and Hidden Markov Models. This paper proposes the use of abductive networks to the problem. We studied the performance of abductive network architecture on a dataset of 21120 samples of handwritten 0-9 digits produced by 44 writers. We developed a new feature set using histograms of contour points chain codes. Recognition rates as high as 99.03% were achieved, which surpass the performance reported in the literature for other recognition techniques on the same data set. Moreover, the technique achieves a significant reduction in the number of features required.

Keywords— Abductive network, Arabic digit recognition

I. INTRODUCTION

Handwritten numeral recognition systems have contributed significantly to progress in the automation process and have improved the interaction between man and machine in many applications, including cheque verification and a large variety of banking transactions, business and data entry applications. Over the past few decades, several approaches have been proposed for pre processing, feature extraction, classification, post-processing of handwritten text, and standard image databases were developed for evaluating the performance of such system [1]. However, most of such research activities have been limited to Latin, Japanese and Chinese text, with little work done on Arabic text including Arabic (Indian) numerals. This may be partially due to the fact that no generally accepted databases existed for Arabic text/numeral recognition that was freely available to researchers [1]. Therefore, various research groups working in the field had to develop their own datasets, which is tedious work. Moreover, performance of various techniques on different datasets may not be directly comparable.

This paper explores the use of an abductive network approach for recognizing handwritten Arabic (Indian) numerals zero to nine (0-9) used in Arabic writing as shown in Figure 1. Following a review of related earlier work in Section 2, Section 3 introduces abductive network modelling. Section 4 describes the handwritten Arabic (Indian) numerals dataset used and the proposed feature extraction techniques. Section 5 summarises the experimental work using abductive machine learning and the results obtained. Finally, section 6 concludes the paper.

II. RELATED WORK

In recent years some researchers have developed computational intelligence models for the accurate recognition of Arabic text. Al-Omari [2] used an average template-matching approach for recognizing Arabic (Indian) numerals. Feature vectors representing significant boundary point distances from the digit centre of gravity (COG) were extracted and used to derive a model for each numeric digit. Classification was performed using the Euclidean distance between the feature vector of the test samples and the generated models. Similarly, Sadri et al. [3] proposed the use of support vector machine for the recognition of isolated handwritten Arabic/Persian numerals. The method views each digit from four different directions, extracting 64 features used to train SVM classifiers to separate the various digit classes. An average recognition rate of 94.14%, was obtained. A new method for recognition of isolated handwritten Arabic (Indian) numerals using Hidden Markov Models (HMM) was presented by Mahmoud [4]. In his method, four sets of features, i.e. angle, circle, horizontal and vertical (ACHV), were generated based on the segmentation of digit pixel image, and for each segment the ratio of black pixels to segment size was computed. These features were used for training and evaluating the HMM models. Average recognition rate of 97.99% was achieved.

Recently, abductive networks have emerged as a powerful tool in pattern recognition, decision support, classification and forecasting in many areas [5], [6], [7]. Inspired by promising results obtained in other fields, we explore the use of this approach for the recognition of handwritten Arabic (Indian) numerals.

9876543210
Figure 1: Handwritten Arabic (Indian) digits 0 to 9
III. ABDUCTIVE NETWORK MODELLING

The abduictory inductive mechanism (AIM) is a supervised inductive learning tool for automatically synthesizing network models from a database of input-output examples [8]. The model emerging from the AIM synthesis process is a robust and compact input-output transformation in the form of a layered abductive network of functional elements as shown in Figure 2. The approach is based on the self organizing group method of data handling (GMDH) [9]. The GMDH approach is a proven concept for iterated polynomial regression that can generate polynomial models in effective predictors. The iterative process involves using initially simple regression relationships to derive more accurate representations in the next iteration in an evolutionary manner. The algorithm selects polynomial relationships and input combinations that minimize the prediction error in each phase. This prevents exponential growth in the polynomial model generated. Iteration is stopped automatically at a point in time that strikes a balance between model complexity for accurate fitting of the training data and model simplicity that enables it to generalise well with new data. A detailed description of the steps of classical GMDH algorithm can be found in [9].

To build GMDH-based abductive network, a training database of input-output information is required. Optimum AIM models are automatically determined using well-proven optimisation criteria, and only input variables that contribute significantly to the model are selected. AIM also adopts a well-defined automatic stopping criterion by minimizing the predicted square error (PSE) criterion [8] that penalises model complexity to keep the model as simple as possible for best generalization. The PSE consists of two terms:

\[
PSE = FSE + CPM (2\sigma^2/N) K
\]  

(1)

Where \( FSE \) is the average fitting squared error for the network on the training data and \( CPM \) is the complexity penalty multiplier, \( K \) is the number of coefficients in the network, and \( \sigma^2 \) is a prior estimate of the model error variance. Training is automatically stopped to ensure a minimum value of the PSE for the CPM parameter used, which has a default value of 1.

The used version of AIM supports several functional elements [8], including: A Normaliser which transforms the original input into a normalized variable having a mean of zero and a variance of unity. A Unitizer which restores the results to the original problem space. And Single, Double and Triple elements which implement a third-degree polynomial expression with all possible cross-terms for one, two, and three inputs respectively; for example,

\[
\text{“Single” Output} = z_0 + z_1x + z_2x^2 + z_3x^3
\]

(2)

Where \( x \) is the input to the element and \( z_0, z_1, z_2 \) and \( z_3 \) are the coefficients of the single element that are determined during training.

Figure 2: A typical AIM abductive network model showing various types of functional elements

IV. THE DATASET AND FCC FEATURE EXTRACTION

To evaluate and compare the performance of the proposed approach we used the dataset of handwritten Arabic (Indian) numerals developed by Mahmoud [10]. The dataset was collected from 44 writers; where each writer wrote 48 samples of each digit (0–9), i.e. 480 digits per writer; for a total of 21,120 digits. The dataset was split into a training set of 15840 cases and an evaluation of 5280 cases. We adopted the same splitting used by earlier published work using the dataset to allow direct comparison of results. A simple and effective feature set was developed using histograms of contour points Freeman’s chain codes.

The digit pixel image was first normalised to 60x60 pixels and its contour points were determined. The contoured image was then segmented into 4x4 blocks (in other experiments 2x2 and 3x3 blocks division were used) in each block the contours were traced with chain codes assigned to the different directions of the contour points using 8-directional path Freeman’s chain code algorithm (FCC) [11]. Finally the frequencies of these codes in each block were horizontally concatenated for all blocks preserving the relative position of the blocks, to give the full feature set for the digit.

Figure 3 shows the outline of the feature extraction of the contour points chain codes applied to a handwritten Arabic (Indian) digit 2. Figure 3a shows contour points of a normalised pixel image of digit and Figure 3b shows contour tracing in the top left block of the pixel image. Figure 3c shows the FCCs and their corresponding frequencies for the same block. In each block an array of eight integer values representing the frequencies of the FCC codes is recorded and these frequencies are horizontally concatenated for all blocks to represent the new feature set. Hence, for a 4x4 blocks a total of \( 4 \times 4 \times 8 = 128 \) features is
generated. Similarly, 32 features and 72 features were generated for 2x2 and 3x3 block segments, respectively.

![Figure 3: Representation of the contour points FCC feature extraction process for a sample handwritten Arabic (Indian) digit 2](image)

**V. EXPERIMENTS AND RESULTS**

This section describes the development of abductive networks for recognition of the handwritten Arabic digits using the feature set generated in section 4. Initially, the 32 features generated using the 2x2 block segments were used to synthesize an abductive network model. The full training set was used to develop 10 abductive networks, one for each of the 10 digits with all the 32 features enabled as network inputs. Figure 4 shows the abductive network model synthesized using CPM=3.5. The numbers (e.g. Var_1) indicated at the model input represent the feature selected as input to the model during training, while Var_33, Var_34, ..., Var_42 represent the 10 network outputs corresponding to digits 0, 1, 2, ..., 9 respectively. It is noted that the model uses 29 inputs out of the 32 inputs which indicates that almost all the features are relevant, with only little redundancy in the feature set. During model evaluation using the evaluation set, the winner-takes-all approach was used to determine the output of the combined model as the digit whose network has the largest output among the models for the 10 digits. Average recognition rate of 99.03% was obtained.

The same experiment was repeated using the 72 and 128 features generated from 3x3 and 4x4 block segments respectively. An average recognition rate of 98.92% and 98.67% was achieved with an optimum abductive network model synthesized with CPM=1. Figure 5 shows the comparison of recognition rate for the 3 different contour points chain codes feature sets. Finally, the recognition rates of other modelling tool used previously on this dataset were compared with that of abductive models synthesized in this work as shown in Figure 6 and Table 1. The comparison indicates that the feature set developed in this work along with the abductive network classifier performed much better in terms of recognition rate and with a significant reduction in features.

![Figure 4: Structure of three of the ten abductive networks synthesized with CPM = 3.5. Var_33 is digit 0 and Var_42 is digit 9.](image)
TABLE I. PERFORMANCE COMPARISON OF OTHER CLASSIFIER AND FEATURE WITH OUR MODEL

<table>
<thead>
<tr>
<th>Network Classifier</th>
<th>Feature type</th>
<th>Number of Feature Used</th>
<th>Average Recognition rate %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abductive Network</td>
<td>Contour points chain codes features</td>
<td>32</td>
<td>99.03</td>
</tr>
</tbody>
</table>

VI. CONCLUSIONS

This paper demonstrates the use of abductive machine learning techniques for the recognition of handwritten Arabic (Indian) numerals. An average recognition rate of 99.03% was achieved with a set of only 32 features based on FCC codes. This result indicated that our proposed feature set and abductive network approach yields a better performance compared to the 97.99% reported in [4] using Hidden Markov model with 120 ACHV features. The experiments conducted also show the power of the abductive approach in automatically selecting the best features, thus achieving a significant data reduction. Future work will consider the possibility of extending the approach to the recognition of handwritten Arabic text.

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