

# Two Dimensional Auto Regressive Model for Hand Writing Recognition

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**Abstract:** The problem of writer identification in a multi-script environment is attempted using a two dimensional (2D) autoregressive (AR) modeling technique. Each writer is represented by a set of 2D AR model coefficients. A method to estimate AR model coefficients is proposed. This method is applied to an image of text written by a specific writer so that AR coefficients are obtained to characterize the writer. For a given sample, AR coefficients are computed and its L2 distance with each of the stored (writer) prototypes identifies the writer for the sample. The method has been tested on datasets of two different scripts, namely RIMES containing 382 French writers and ISI consisting of samples from 40 Bengali writers.

**Keywords:** AR Coefficient, Classification, Hand writing, Pattern Recognition

## 1. Introduction

We are dealing with the problem in which we have a database consisting of writing of different authors written in different script. At this point we are given an image sample of an unknown author and by applying our proposed method we have to tell who this author in our database is. Essentially as any image (may be of handwriting or of something else is) a sequence of pixel values, we can look upon them as sequence of random variables where each random variable corresponds to a fix cell. Previous method which people have applied to solve this problem is that they have viewed hand writing image as a sequence of pixel value and they have tried to predict value of a pixel location by using previous say n terms.

Let for the k th location we want to predict its pixel value say  $y_k$  by using previous n terms. Let  $y_k$  can be written as

$$Y_k = a_1 Y_{k-1} + a_2 Y_{k-2} + \dots + a_n Y_{k-n} + \epsilon_k \quad [1]$$

Let these  $a_i$ 's,  $i=1,2,\dots,n$  are such that they are best to predict pixel value of all location then this coefficient vector  $(a_1, a_2, \dots, a_n)$  are said to be AR coefficient of this image or image signal.

AR coefficient [2] for each image represents that particular writer. Now for the unknown sample it's AR coefficients are calculated and it's Euclidean distance with AR coefficients of all other images are calculated and whichever is find to be minimum is declared to be writer of that sample.

Now in our method what we do, instead of choosing neighboring pixel as previous say n-terms we choose a rectangular neighborhood of size say  $(m \times n)$ . Clearly the

more and more number of terms we take in order to predict a pixel value the more accuracy we achieve but at the same time it would increase our computational complexity to a greater extent so there is a trade-off between size of the neighbor set and accuracy we want to achieve. The question arises at this point, Does there exist an optimal choice of neighbor for solving this problem More over if we choose our nbd-set in a square or rectangle e.g.  $4 \times 4$ ,  $3 \times 5$ ,  $5 \times 3$ , this enhances our difficulty to some more extent because while implementing we see that not only size but shape also affects our calculated result for example  $3 \times 5$ ,  $5 \times 3$  both nbd set has 14 pixel value for predicting a particular location but both gives different results while using [4].

So, at this point not only size but shape also is a parameter which we need to take care of.

## 2. Method

### 2.1 Two Dimensional Autoregressive Model

A discrete image defined on an  $M \times N$  (say,  $P = M \times N$ ) rectangular grid is denoted by  $\{x_{ij}\}$  ( $i = 1, 2, \dots, M$ ;  $j = 1, 2, \dots, N$ ). When each element  $x_{ij}$  is a random variable,  $\{x\}$  is called a discrete random field. [5]

In this paper, we deal with a class of random linear equation.

$$x_{ij} = \sum_{(p,q) \in D} \theta_{pq} x_{i-p, j-q} \quad (1)$$

where  $D$  denotes the context region. Normally (but not necessarily)  $D$  is represented by a rectangular region as  $D = \{(p, q) \mid -m \leq p \leq m, -n \leq q \leq n, (p, q) \neq (0,0)\}$

$\theta$  is the AR model coefficients and  $p$  is the order of the model. So value of each pixel (say,  $y = x_{ij}$ ) is predicted as a linear combination of  $D$  neighboring pixels. So in general

we can write

$$y = h \theta \tag{3}$$

$h$  is the  $D \times 1$  vector of the  $D$  neighboring pixels and  $\theta$  is the  $1 \times 1$  scalar of the AR model coefficients. For each of these  $P$  pixels, values of the  $D$  neighboring pixels are recorded in each row of  $h$ .

### 2.2 Estimation of AR Coefficient

Next, our problem is to estimate  $\theta$ . We present this estimation by following a bra-ket notation. Let  $e$  denote the error in predicting the value of pixel,  $y$ . So we can write

$$e = y - h\theta \tag{4}$$

the squared error is defined as

$$J = \{e^2\} \tag{5}$$

so

$$\begin{aligned} J &= \langle y - h\theta | y - h\theta \rangle \\ &= \langle y | y \rangle - \langle y | h\theta \rangle - \langle \theta h^T | y \rangle + \langle \theta (h^T h) \theta \rangle \\ dJ &= -2 \langle y h | d\theta \rangle + 2 \langle \theta | h^T h | d\theta \rangle \end{aligned}$$

To minimize  $J$ ,  $dJ$  is set to zero i.e

$$\begin{aligned} \langle y h | &= \langle \theta | h^T h | \\ \Rightarrow (h^T h) | \hat{\theta} \rangle &= h^T | y \rangle \tag{6} \\ \Rightarrow | \hat{\theta} \rangle &= (h^T h)^{-1} h^T | y \rangle \end{aligned}$$

So estimation of  $\theta$  requires matrix multiplications, transpose and inversion operations. This solution is simply the least mean square solution of equation (3).

### 2.3 Writer Identification

AR coefficients computed from an image written by a specific writer characterize that writer. Say, there are  $w$  writers; each of them contributes one sample. Let  $\theta_i$  be the estimated AR model coefficients for the  $i^{\text{th}}$  writer. For an unknown sample, at first the AR model coefficients are computed. Let  $\hat{\theta}$  be the estimated coefficients for this sample. Next, the Euclidean distance between this sample and any of the  $N$  samples of the reference database is computed as follows

$$d(\hat{\theta}, \hat{\theta}_i) = \|\hat{\theta} - \hat{\theta}_i\|^2 \tag{7}$$

It is decided that the given sample is written by the  $j$ -th writer if

$$d(\hat{\theta}, \hat{\theta}_j) < d(\hat{\theta}, \hat{\theta}_i) \forall i, i \neq j.$$

### 3. Experimental Results

The capability of the method in handling multi-script environment is tested by mixing the RIMES and ISI samples together. Therefore, number of writers in this mixed dataset becomes 422 (382 French and 40 Bengali writers). Test set contains 140 samples (100 French and 40 Bengali). The identification results are reported in Table-1. Accuracies are 61% and 95% corresponding to the consideration of only the top choice and the top 10 choices. This clearly shows that multi-script handling capability of the method. The identification performance is comparable to the results obtained for a single script.

Next, the results obtained using the three context patterns are integrated through voting method. Table-2 presents the results obtained after combining the results achieved by three different pixel templates. It is noticed that identification accuracies are improved due to this combination. When individual results are integrated, the accuracy is increased by 1% to 2% at different number of top choices.

**Table 1:** Writer identification results on RIMES+ISI dataset

Context Type (all at 300 dpi)	Recognition Results (% correct) on Mixed Dataset # Writers: 422, # Test samples: 140					
	Top 1	Top 2	Top 3	Top 4	Top 5	Top 10
C <sub>1</sub>	58.6	70.1	71.4	72.1	75	88.6
C <sub>2</sub>	60.7	69.3	76.4	79.3	79.3	90.7
C <sub>3</sub>	60.7	65.7	71.4	75.7	77.1	95

**Table 2:** Writer identification results on RIMES+ISI dataset after classifier combination

Recognition Results (% correct) on Mixed Dataset					
# Writers: 422, # Test samples: 140					
Top 1	Top 2	Top3	Top4	Top 5	Top 10
62.1	70.7	77.9	80.7	81.4	96.4

#### 4. Conclusion and Future Scope

The method proposed here has been purely statistical and seems more plausible because it takes into account the neighboring from all possible direction and not only the previous few terms. It facilitate us to choose different shape and size of neighbors rectangular square of whatsoever. Also the experimental result suggests that it has been efficiently effective on the mix of two different scripts viz Bengali and French.

As for the future work is concerned it does not give us an optimal choice of neighbors among all possible neighbors it only works on the basis that the bigger size of neighbors we choose for working the more accuracy we would get provided we can afford the computational overhead.

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