Genetic Algorithm Approach to Identify Englishlike Written Character

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Abstract:*In the present digital time most of the document and papers are scanned or taking a photo as input and using some communication medium send to the other user.But few people have capability to copy hand written signatures or characters and also copy the pattern of the signatures or characters and words. Some time it is very difficult to make differentiate between the original handwritten signatures or characters (is written by authorized person) and duplicate hand written signatures orcharacters (is written by unauthorized person). In this situation we try to apply machine learning approach like Forward Algorithmof Hidden Markov Model, Baum Welch and Genetic Algorithm etc. In this paper we use computational approach for identification of the original and hand written characters with the help of different approaches. Every approach obtained separate results.*
Keyword:*HMM (Hidden Markov Model), GA (Genetic Algorithm), Handwritten Character Recognition (HC).*

I. Introduction

Hand written characters' recognition model will be successful if model application has to be ability of acquire and detect Characters in proper manner, as proper documents, proper in pictorial form, efficiently convert into machine encoding. All machine learning approaches is based on the artificial intelligence, computer performance, and pattern analysis ability. Characters recognition approaches also depends on the behavior and psychology of the person, the person set the problems. Every machine learning model gives the results of specific data set related to that problem at the time learning stage. One model is learned to provide answers of the data it has learned. After learning model gives results on unseen data with high quality.

II. Hidden Markov Model

An HMM is a probabilistic sequence model: given a sequence of units (words, letters, morphemes, sentences, whatever), they compute a probability distribution over possible sequences of labels and choose the best label sequence.

A Hidden Markov Model is a stochastic model where the states of the model are hidden. Each state can emit an output which is observed. This type of models work on temporal or sequential data. It provides a way to model the dependencies of current′ information with previous information. It is composed of states, transition scheme between states, and emission of outputs (discrete or continuous). Several goals can be accomplished by using Markov models [30, 31]:
1. Learn statistics of sequential data.
2. Do prediction or estimation.
3. Recognize patterns.

HMM Mathematical Model:
From Bayes' Theorem, we can obtain the probability for a particular as [32, 33]:

$P\,(q_i\,/o_i) = \frac{P\,(o_i/q_i)\,P(q_i)}{P(o_i)}$

For a sequence of length t:

$P\,(q_1\ldots q_t/o_1\ldots o_t) = \frac{P\,(o_1\ldots o_t/q_1\ldots q_t)\,P(q_1\ldots q_t)}{P\,(o_1\ldots o_t)}$

From the Markov property:

$P\,(q_1,\ldots,q_t) = \prod_{i=1}^{t} P(q_i\,|q_{i=1})$

Independent observations assumption:

$P\,(o_1\ldots o_t/q_1\ldots q_t) = \prod_{i=1}^{t} P\,(q_i\,/o_i)$

Thus:
$$P(q_1 \ldots q_t / o_1 \ldots o_t) \propto \prod_{i=1}^{t} P(q_i \mid q_{i=1}) \prod_{i=1}^{t} P(q_i / o_i)$$

HMM Parameters:
1. Transition probabilities $P(q_i \mid q_{i-1})$
2. Emission probabilities $P(o_i \mid q_i)$
3. Initial state probabilities $P(q_i)$

A HMM is governed by the following parameters: $\lambda = \{A, B, \pi\}$
1. State-transition probability matrix A
2. Emission / Observation / State Conditional Output probabilities B
3. Initial (prior) state probabilities π

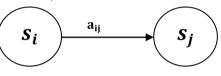**Determine the fixed number of states (N):**
$S = (s_1, \ldots, s_N)$

State-transition probability matrix:

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{1N} \\ a_{21} & a_{22} & a_{2N} \\ a_{N1} & a_{N2} & a_{NN} \end{bmatrix}$$

$\sum_{j=1}^{N} a_{ij} = 1$ (Each row/Outgoing arrows)

$a_{ij} = (q_t = s_j \mid q_{t-1} = s_i), 1 \leq i,j \leq N$

$a_{ij} \geq 0$

$a_{ij} \rightarrow Transisiton probability from state s_i to s_j$

III.   Implementation

In Implementation of Genetic Algorithm, we have taken the state transition matrix A used in Hidden Markov Model (as described earlier). The crossover operation is applied on the state transition matrix A to generate the random population. The value of P (O|λ) is calculated for all these random populations. The state transition matrix A corresponding to the maximum value of P(O|λ) is further taken for creating the next set of population by using crossover and mutation operation simultaneously. After the creation of these populations again value of P(O|λ) are calculated and the corresponding value of state transition matrix A is taken for further population generation. This process continues until we get the optimum value of P(O|λ).The state transition matrix A is shown below. Each row of matrix A is considered as Chromosome. Each specific arrangement of these chromosomes is termed as a single population.

A= {a_{ij}}. In this table the value of i=1 to 8 and the value of j=1 to 8. All rows are representing new generations of population with modified fitness [7,8].

Table1. Initial state transition probability matrix depicting the chromosomes

	S1	S2	S3	S4	S5	S6	S7	S8
S1	0.1	0.2	0.2	0	0	0	0	0.5
S2	0.2	0.1	0.5	0	0	0	0	0.2
S3	0	0	0.1	0.4	0	0	0.4	0.1
S4	0	0	0	0.1	0.5	0.4	0	0
S5	0	0	0	0.6	0.1	0	0.3	0
S6	0	0	0	0.3	0.3	0.1	0.6	0
S7	0	0	0.15	0.15	0	0.3	0.1	0.3
S8	0.3	0.1	0.1	0.1	0	0	0.3	0.1

IV.   Genetic Algorithms

A Genetic algorithm GA is a search method of natural selection. This type of search method is applied to find the optimize solutions of problems. Genetic Algorithms is a subset of Evolutionary algorithms. EA generates solutions to optimization problems using techniques inspired by natural evolution, such as Inheritance, mutation, selection and crossover. In a genetic algorithm, each candidate solution has a set of properties. Properties of candidate are known as chromosomes or genotype. Candidates can be mutated and altered traditionally. First we randomly select candidates for mutation from the population via iterative process. Filtered populations of candidate come after iteration process is known as generation [1, 2,3]. After that evaluates fitness of every individual in the population. Usually fitness value of objective function is being solved. The more fit

individuals are selected from the current population, and each individual's genome is modified to generate new generation. For the next generation old generation is used as population. In this way every generation will be modified population from the old population and refined. The algorithm finished when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population [7,8]. We can better realize the genetic algorithms flow with the help of below picture.

Crossover: To generate random population we applied crossover operation on state transition matrix A. For that we have selected two random chromosomes (among 1 to 8) and interchange their position. State transition matrix A after interchanging chromosome 3 and 5.
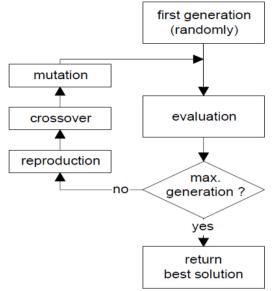

Figure1. Flow chart of Genetic Algorithm.

Table2. Matrix A after applying Crossover operation

	S1	S2	S3	S4	S5	S6	S7	S8
S1	0.1	0.2	0.2	0	0	0	0	0.5
S2	0.2	0.1	0.5	0	0	0	0	0.2
S3	0	0	0.1	0.4	0	0	0.4	0.1
S4	0	0	0	0.1	0.5	0.4	0	0
S5	0	0	0	0.6	0.1	0	0.3	0
S6	0	0	0	0.3	0.3	0.1	0.6	0
S7	0	0	0.15	0.15	0	0.3	0.1	0.3
S8	0.3	0.1	0.1	0.1	0	0	0.3	0.1

Mutation: Mutation is applied on state transition matrix A by adding or subtracting a small number d in the range of (0.001-0.009) from any randomly generated row and column. State transition matrix A after mutating the value A (3, 5) by d=0.003.

Table3. Matrix A after applying Mutation operation

	S1	S2	S3	S4	S5	S6	S7	S8
S1	0.1	0.2	0.2	0	0	0	0	0.5
S2	0.2	0.1	0.5	0	0	0	0	0.2
S3	0	0	0.1	0.4	0	0	0.4	0.1
S4	0	0	0	0.1	0.5	0.4	0	0
S5	0	0	0	0.6	0.1	0	0.3	0
S6	0	0	0	0.3	0.3	0.1	0.6	0
S7	0	0	0.15	0.15	0	0.3	0.1	0.3
S8	0.3	0.1	0.1	0.1	0	0	0.3	0.1

Training: For training we have used the above described procedure until the optimum value of $P(O|\lambda)$ is calculated. Table listed below shows the optimum values of $P(O|\lambda)$ obtained after applying the above described procedure are on ten images of English character **A**. Result shows that range for English character **A** will be **0 to 13.101611.**

Table4.P $(O|\lambda)$ values of ten images of character **A** by using Genetic algorithm

Image Number	Optimum value of P(O|λ)	Value after subtracting the MAX value
1	45.931374793766658	5.951343101964568
2	45.024052893630682	5.044021201828592
3	53.081643153039984	13.101611461237894
4	46.293857621043280	6.313825929241190
5	44.491400874619245	4.511369182817155
6	46.841130028390438	6.861098336588348
7	39.980031691802090	0
8	46.456143959079796	6.476112267277706
9	43.597508500817824	3.617476809015734
10	43.961701605892614	3.981669914090524

Testing: For testing, we input an image of new character and calculate the optimum value of P(O|λ). We subtract this value from the maximum P(O|λ) value that we got during the training of that character, if the result lies in our already calculated range this implies that we have recognized character accurately, else our model fails to recognize that image correctly.Table5 listed below shows the value of P(O|λ) calculated for six test images of English character **A** after subtracting them from the MAX value which was obtained during the time of training.

Table5. Result obtained by genetic algorithm

Test Image Number	Value of P(O|λ) after subtracting from the MAX value	Recognized
1	-1.750567630343475	No
2	3.970562730108057	Yes
3	7.262407602282607	Yes
4	2.282290161880660	Yes
5	7.483495368462940	Yes
6	8.002883980225448	Yes

V. Conclusion And Future Work

Above result shows that five values out of six values lie in the range created for English character **A**. It shows that our model has efficiency of 83.33% (approx.) in recognizing the English character **A.**In order to resolve the real-life problem of character recognition, some other techniques must be introduced to describe a large number of similar structures which belong to the same category of characters; we must also allow distinct descriptions among different patterns of characters. We can say that a combined recognition model will provide a solution to a real-life handwritten character recognition problem. The best method of solving the problem of character recognition is to combine the HMMs at different levels of GA iteration [1].

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