Segmentation free Bangla OCR using HMM: Training and Recognition

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ABSTRACT

The wide area of the application of HMM is in Speech Recognition where each spoken word is considered as a single unit to be recognized from the trained word network. Using this concept some research has been done for character recognition. In this paper, we present the training and recognition mechanism of a Hidden Markov Model (HMM) based multi font supported Optical Character Recognition (OCR) system for Bangla character. In our approach the central idea is separate HMM model for each segmented character or word. We emphasize on word level segmentation and like to consider the single character as a word when the character appears alone after segmentation process is done. The system uses HTK toolkit for data preparation, model training from multiple samples and recognition. Features of each trained character are calculated by applying Discrete Cosine Transform (DCT) to each pixel value of the character image where the image is divided into several frames according to its size. The extracted features of each frame are used as discrete probability distributions that will be given as input parameter to each HMM model. In case of recognition a model for each separated character or word is build up using the same approach. This model is given to the HTK toolkit to perform the recognition using Viterbi Decoding. The experimental result shows significant performance.

Key Words: Optical Character Recognition (OCR), Hidden Markov Model (HMM), HTK, Discrete Cosine Transform (DCT).

1. Introduction

Hidden Markov Models (HMM) is widely using in developing continuous speech recognition (CSR) technology which has several useful aspects, including language-independent training and recognition methodology; automatic training on non-segmented data; and simultaneous segmentation and recognition. However, other applications including speech synthesis, character recognition and DNA sequencing are also using HMM. We use the concept of applying HMM Technique for speech recognition into our training and recognition methodology of OCR where the similar approach is used in some research of building language independent OCR system [1] and High accuracy off-line cursive handwriting recognition [2]. We follow the concept of Speech Recognition where each word is considered as a single unit to be recognized from a sentence uttered. In our approach, we create a model for each individual character or word where the character is considered as a word only at the time when it segmented separately from a segmented line at the time of recognition. Here we give emphasize on word level segmentation technique because in case of Bangla Optical Character Recognition segmentation is a significant issue that is still a vast challenge to resolve accurately. In Bangla script, the position of the dependent vowels and diacritics marks and the existence of touching characters in the scanned document make the task of segmenting the words into character level very complex. Many works has been done for character level segmentation [3 - 7]. Some approach can separate the character successfully but in application level due to the presence of noise, accuracy of performance and considering the cost of computation we choose word level segmentation approach. We should note that this is the first reported attempt at creating a HMM based segmentation free OCR for Bangla script.

We use HTK Toolkit for implementing our application after completing the preprocessing and feature extraction steps. Preprocessing includes binary image conversion, noise removing from image, skew correction, segmentation that includes line separation, word separation and character separation. The segmented portion is then converted into image array that contains binary values for each pixel. Note that in our approach the segmented character is obtained by considering the image boundary not the connected component approach. The next step is to divide the image array into certain number of frames that will be considered as the number of states for the HMM model of the segmented image. Then Feature extraction is performed using Discrete Cosine Transform (DCT) calculation on each individual pixel of each frame that modifies the pixel value in each frame accordingly. These newly calculated pixels value will be considered as discrete probability distributions which will be given as input parameter to each HMM model.

HTK Toolkit does the procedure of creating a particular model from the number of samples that is provided as training input and then save this model description into appropriate files. Based on the number of samples the model parameters (means and variance) will be estimated by internal command of HTK Toolkit. However, for recognition a temporary HMM model is build from the word or character image using the same procedure described above. Then the recognition is performed using Viterbi decoding by HTK Toolkit.

The post processing includes taking the appropriate Unicode characters from the model database against each model name that is determined by the recognition tools of HTK. Then these characters are stored and written into file sequentially.

The flow chart for training and recognition is shown in Figure 1 that clearly visualizes the actual procedure of training and recognition.

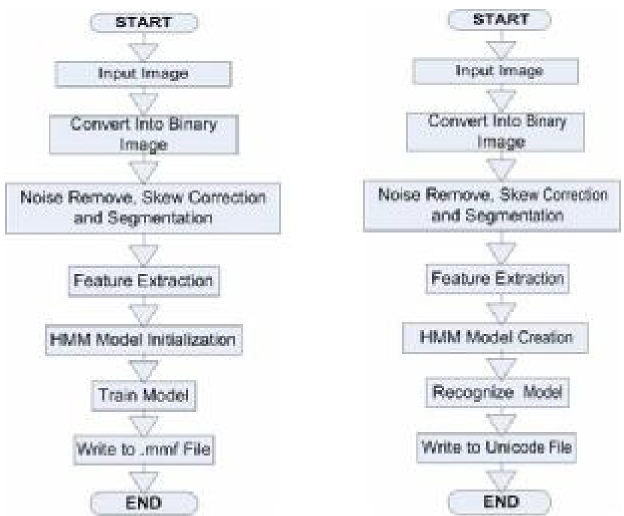

Figure 1: Flow Chart of Training and Recognition Procedure

2. Related Works

Varieties of different approach have been applied for the recognition process of OCR. In [3] the character shapes are recognized by a combination of template and feature matching approach, where the character recognition involves separation of compound characters from the basic ones. A structural-feature-based tree classifier has been used in [4] to recognize the basic characters where in case of compound characters, feature based tree classifier is initially used to separate them into small groups and next, an efficient template matching approach is employed to recognize individual character.

Neural Network approach has been used for classification and recognition where training and Recognition phase of the neural network has been performed using conventional back propagation algorithm at [7] and using multi-layered feed-forward back propagation neural network at [8].

Hidden Markov Model (HMM) is widely used in the area of research on handwriting recognition [2, 9, and 10] for different languages. Some approach needs one hidden Markov model per word in the vocabulary and during the recognition phase, the word to be recognized is separately scored against all the models. Another approach is to use one model for the entire language. However, research work have been done on building language independent OCR [1], where the system uses hidden Markov modeling (HMM) technology to model each character. The benefit of using this system is that the fundamental models are not designed for any particular language, thus making it possible to apply the same technology to many scripts.

Hidden Markov Model Toolkit (HTK) is mainly used for speech recognition, however some research have been done to use the HTK toolkit for character recognition [11 - 13]. The system extracts a set of simple statistical features from each frame and then injects the sequence of the feature vectors to the Hidden Markov Model Toolkit (HTK). The process has significant similarity with Continuous Speech Recognition (CSR) system.

2. Overview

The entire procedure of recognition and training can be break down into two parts based on HTK Toolkit point of view. The first part consists of preprocessing up to Feature calculation and the second part consists of HTK Toolkit operation that is different for training and recognition process.

2.1 Segmented Image to Feature Calculation

Here I assume that I already have the segmented image that can be either a character or a word and the image is already converted to binary image. Let take a segmented character and a segmented word that is shown in Figure 2.

2: (a) Segmented character ‘soreo’; (b) Segmented word ‘tumi’

2.1.1 Frame Calculation

Now from these images number of frame will be calculated. In our approach, we choose the frame width to be 8 and the frame height to be 90. The frame width and height is chosen according to our statistical analysis. Based on the frame width and height we divide the segmented image into several frames. The size of mean and variance vector is also determined from the frame width and height. For example the number of frame of the segmented character soreo is 3 and segmented word tumi has 6 frames. Number of frame is most important because it determines the number of states of the HMM model. So we can say that the number of states for hmm model soreo is 3 and tumi has 6 states. The above discussion is illustrated in Figure 3 and Figure 4.

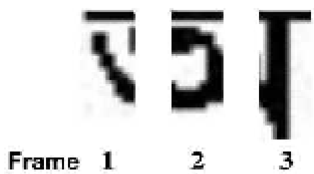

Figure 3: segmented character “soreo” with 3 frames

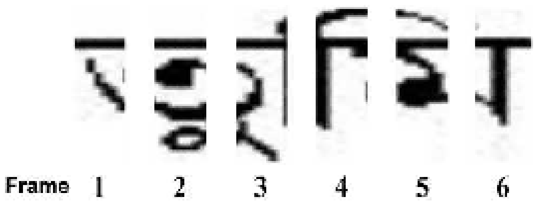

Figure 4: segmented word “tumi” with 3 frames

2.1.2 Feature Calculation

In this phase each frame is taken separately and then the feature calculation is performed on each individual pixels of the frame by applying Discrete Cosine Transform (DCT).

2.1.2.1 Discrete Cosine Transform (DCT)

The discrete cosine transform (DCT) is a technique for converting a signal into elementary frequency components. The DCT represent an image as a sum of sinusoids of varying magnitude and frequencies. The DCT has a property that for a typical image, most of the visually significant information about the image is concentrated in just a few coefficient of the DCT. It is a separable linear transformation; that is, the two-dimensional transform is equivalent to a one-dimensional DCT performed along a single dimension followed by a one-dimensional DCT in the other dimension. The definition of the two-dimensional DCT for an input image A and output image B is

$$B_{pq} = \alpha_p \alpha_q \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} A_{mn} \cos\frac{\pi(2m+1)p}{2M} \cos\frac{\pi(2n+1)q}{2N}, \quad \begin{matrix} 0 \le p \le M-1 \\ 0 \le q \le N-1 \end{matrix}$$

$$\alpha_p = \begin{cases} 1/\sqrt{M}, & p = 0 \\ \sqrt{2/M}, & 1 \le p \le M-1 \end{cases} \qquad \alpha_q = \begin{cases} 1/\sqrt{N}, & q = 0 \\ \sqrt{2/N}, & 1 \le q \le N-1 \end{cases}$$

where M and N are the row and column size of A, respectively. If you apply the DCT to real data, the result is also real. The DCT tends to concentrate information, making it useful for image compression applications.

After applying DCT on the pixels values of each frame the updated information is stored into a file which will be given as hmm model input for the particular character or word that is considered to be trained.

Up to this stage the image processing methodology is exactly same for both the operation of training and recognition. The only difference is that, training mechanism uses a certain number of samples for modeling a particular character or word that is used for estimating model parameters in HTK Toolkit but recognition mechanism create model only for the particular image character or word to be recognized.

So at this stage we can create HMM model for the character “soreo” and word “tumi” which is shown in Figure 5 and Figure 6.

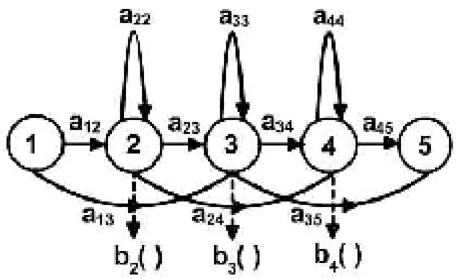

Figure 5: HMM model for character “soreo”

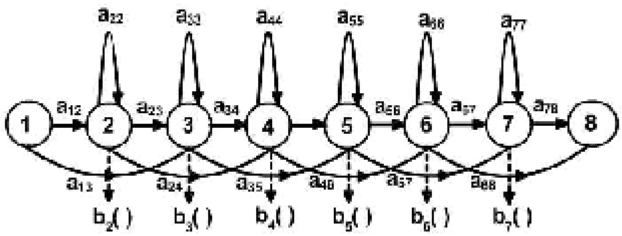

Figure 6: Hmm model for word “tumi”

These models clearly proof the description of the framing and feature extraction methodology described above. We can see from these models that the segmented character “soreo” has 3 states without the start and end state that is common to each model. Similarly the segmented word has 6 states without the start and end states. Now the HMM model components (number of states and calculated feature values) for the segmented character and word constructed in this stage is ready to be given as HTK

Toolkit input for initializing the HMM model or performing the recognition task.

2.2 HTK Toolkit Operations for Training and Recognition

2.2.1 The HTK Toolkit

The Hidden Markov Model Toolkit (HTK) is a portable toolkit for building and manipulating hidden Markov models (HMM). HTK is primarily used for speech recognition research although it has been used for numerous other applications including research into speech synthesis, character recognition and DNA sequencing. HTK is in use at hundreds of sites worldwide.

HTK consists of a set of library modules and tools available in C source form. The tools provide sophisticated facilities for speech analysis, HMM training, testing and results analysis. The software supports HMMs using both continuous density mixture Gaussians, discrete distributions and can be used to build complex HMM systems.

Parts of HMM modeling using HTK Toolkit are divided into four phases [14]:

1. Data Preparation
2. Model Training
3. Pattern Recognition
4. Model Analysis

2.2.1.1 Data Preparation

In the Data Preparation stage, first we will define a word network using a low level notation called HTK Standard Lattice Format (SLF) in which each word instance and each word-to-word transition is listed explicitly. This word network can be created automatically from the grammar definition. At this same stage, we have to build a dictionary in order to create a sorted list of the required character or words to be trained. Then we will use the tool HSGen to generate the prompts for test sentences. Note that the data preparation stage is required only for recognition purpose. It has absolutely no usage for the training purpose.

2.2.1.2 Model Training

The first task is to define a prototype for the HMM model to be trained. This task will depend on the number of states and the extracted feature of each character or word. The definition of a HMM must specify the model topology, the transition parameters and the output distribution parameters. HTK supports both continuous mixture densities and discrete distributions. In our application we will use discrete distributions as we see that the observation state is finite for each frame (8 x 90 = 720 states). Then we have to initialize the estimation of the HMM model parameters. The model parameters contain the probability distribution or estimation of each model. By far the most prevalent probability density function is the Gaussian probability function that consists of means and variances and this density function is used to define model parameters by the HTK. For this we have to invoke the tool HInit. After the initialization process is completed the HMM model is written into .mmf file that contains all the trained models and is used in recognition.

2.2.1.3 Pattern Recognition

Comparative to the training, recognition is much simpler. To complete this task we have to create a HMM model of the character or word image. Then this model will match with all the HMM models and the most likely model will be given as output. To perform this task using HTK we have to invoke the recognition tool HVite that uses the word network describing the allowable word sequence build up from task grammar, the dictionary that define each character or word, the entire list of HMMs and the description of each HMM model. HVite is a general-purpose Viterbi word recognizer. It will match a HMM model against a network of HMMs and output a transcription for the recognized model into a Master Label File .mlf.

After the recognition process is completed, the model name is read from the Master Label File (.mmf) and the associated

Unicode character for the recognized model is written to the output file.

3. Performance Analysis:

In our approach the performance of the recognizer depends on the number of trained characters and words. Usually the recognizer does not give any transcription as output if the hmm model for the character or word to be recognized not likely to the trained models of the system. In some cases the recognizer give wrong output when the HMM model to be recognized not trained previously and there exists a similar type model in the system. In such case HTK output a transcription to which the model is most likely that means when the score of the model exceeds the threshold value. So we can say that the recognizer produce maximum performance when the system is trained with a large training corpus.

Here we start with an example that shows the performance measurement of the recognizer. The test image to be recognized is shown in Figure: 8.

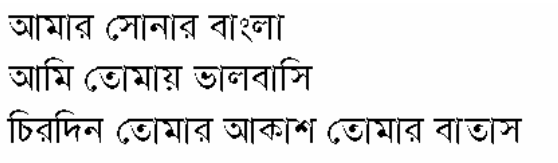

Figure 8: Test Image for measuring the performance of the recognizer

Assume that we have a small training corpus is with the models listed in Table: 1.

Word	Model Name	Unicode Sequence
আমার	h0800	0986, 09AE, 09BE, 09B0
সোনার	h0801	09B8, 09CB, 09A8, 09BE, 09B0
বা	h0802	09AC, 09BE
ংলা	h0803	0982, 09B2, 09BE
আমি	h0804	0986, 09AE, 09BF
তোমায়	h0805	09A4, 09CB, 09AE, 09BE, 09DF
ভালবাসি	h0806	09AD, 09BE, 09B2, 09AC, 09BE, 09B8, 09BF
চিরদিন	h0807	099A, 09BF, 09B0, 09A6, 09BF, 09A8
আকাশ	h0808	0986, 0995, 09BE, 09B6
তাস	h0809	09A4, 09BE, 09B8

Table 1: List of existing training models

We can clearly observe from Figure: 8 and Table: 1 that the word তোমার is not trained in the existing corpus. So now the recognizer is not supposed to recognize it. Instead, it will do not provide either any transcription or it can output the transcription of that model which is most likely or the model that is score meet the required threshold. The output from the recognizer with this existing corpus is given Figure: 9

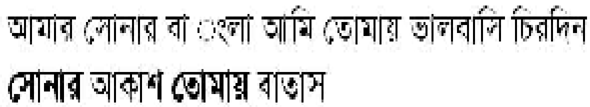

Figure 9: Performance of the recognizer without properly trained

Here we see that the recognizer's output is improper without the training of the word তোমার. In the output we observe that the recognizer output two different words in place of তোমার (In figure: 9 the bold and underline words). So it is proved that without the training the performance is not accurate. To improve performance, the word তোমার have to be trained. Let the model name for the word তোমার is h0810, the Unicode sequence will be 09A4, 09CB, 09AE, 09BE, 09B0. The trained image with thirty samples is shown in Figure: 10

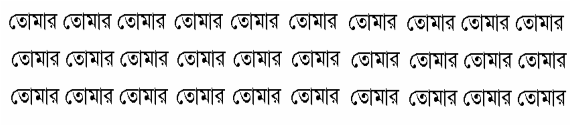

Figure 70: Trained Image of তোমার with thirty samples

Now our training corpus contains all required models to recognize the test image of Figure: 8 with maximum performance. Let us run the recognizer again and observe the performance. The observation result is shown in Figure: 11

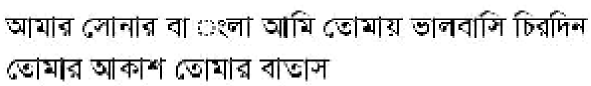

Figure 81: Performance of the recognizer with proper training

The result shows that the performance is improved to maximum level after proper training.

4. Conclusion

Here we present the training and recognition mechanism of the Hidden Markov Model (HMM) based Optical Character Recognizer (OCR) for Bangla character. The system is mainly divided into two parts; one is preprocessing up to feature calculation and the other part consists of HTK Toolkit operations that are used to initialize the HMM model from a certain number of samples and to recognize a particular model. Multi font character recognition depends on training corpus with different font. It shows significant performance for trained character. Performance of the recognizer depends on the number of trained models.

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