SPOTTING MULTILINGUAL CONSONANT-VOWEL UNITS OF SPEECH USING NEURAL NETWORK MODELS

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Abstract. In this paper, we consider an approach for multilingual speech recognition by spotting consonant-vowel (CV) units. The main issues in spotting multilingual CV units are the location of anchor points and labelling the regions around these anchor points using suitable classifiers. The vowel onset points (VOPs) have been used as anchor points. The distribution capturing ability of an autoassociative neural network (AANN) models is explored for detection of VOPs in continuous speech. We consider support vector machine (SVM) based classifiers due to their ability of generalisation from limited training data and also due to their inherent discriminative learning. We study the spotting approach for recognition of a large number of CV units in the broadcast news corpus of three Indian languages.

1 Introduction

The main objective of continuous speech recognition system is to provide an efficient and accurate mechanism to transcribe human speech into text. Typically, continuous speech recognition is performed in the following two steps: (1) speech signal to symbol (phonetic) transformation, and (2) symbol to text conversion. Two approaches are commonly used for subword unit based continuous speech recognition. The first approach is based on segmentation and labelling [1]. In this approach, the continuous speech signal is segmented into subword unit regions and a label is assigned to each segment using a subword unit classifier. The main limitation of this approach is the difficulty in automatic segmentation of continuous speech into subword unit regions of varying durations. Because of imprecise articulation and coarticulation effects, the segment boundaries are manifested poorly. The second approach to speech recognition is based on building word models as compositions of subword unit models, and recognising sentences by performing word-level matching and sentence level matching using word models and language models respectively [1]. The focus of this approach is on recognising higher level units of speech such as words and sentences rather than on recognising subword units.

In this paper, we propose an approach for multilingual speech recognition by spotting subword units. Specifically, we consider a method for spotting subword
units using vowel onset points (VOPs) as anchor points and labelling the regions around these VOPs using suitable classifiers. The important features of spotting approach are that there is no need for automatic segmentation of speech and it is not necessary to use models for higher level units to recognise the subword units. The symbols that capture the phonetic variations of sounds are suitable units for signal to symbol transformation. Pronunciation variation is more systematic at the level of syllables compared to the phoneme level. Syllable-like units such as consonant-vowel (CV) units are important information-bearing sound units from production and perception point of view [2]. Therefore, we consider CV units of speech as the basic subword units for speech recognition. In Indian languages, the CV units occur with high frequency.

The distribution capturing ability of autoassociative neural network (AANN) models is explored for detection of VOPs in continuous speech [3]. An important issue for the development of a suitable classification system for the recognition of CV units in Indian languages is the large number of these units. Combination of more than 30 consonants and 10 vowels of a language result in a set of about 300 CV units. Further, there are many regional languages across the country. Difficulties in the development of multilingual speech recognition systems are due to the presence of several new classes, degree of overlapping of classes and frequency of occurrence of a given class in different languages. The difficulties in designing a multilingual system are also due to variability among the data set, amount of training data and large number of CV classes. Also, many of the CV units have similar acoustic features. Additionally, the number of examples available in a corpus are not same for all the units. There may be many units for which only a small number of examples are available. We consider an approach for development of classification system by combining same type of CV classes across the Indian languages [4]. We consider support vector machine (SVM) based classifiers due to their ability of generalization from limited training data and also due to their inherent discriminative learning [5]. The variability among the data set and more number of classes in multiple languages has less effect on the recognition performance when SVMs are used for classification [4]. We demonstrate the CV spotting based approach to continuous speech recognition for sentences in multiple Indian languages.

The paper is organised as follows: In Section 2, we discuss the issues in spotting CV units. The system for spotting multilingual CV units in continuous speech is described in Section 3. In Section 4, the spotting approach is illustrated with an example. Studies on recognition of CV units by processing the segments around the hypothesised VOPs in continuous speech utterances is also presented in this section.

2 Issues in spotting multilingual CV units

Strategies for spotting subword units in continuous speech have been based on training the classifiers to recognise only the segments of the continuous speech signal belonging to subword units and reject all other segments. The models thus
trained to classify or reject are then used to scan the speech signal continuously and hypothesis the presence or absence of the corresponding subword units. This strategy is similar to the keyword spotting approaches [6]. The main limitation of this strategy based on scanning is that a large number of spurious hypotheses are given by the spotting system [7]. For spotting CV units in continuous speech, we consider an approach based on detection of VOPs and labelling the segments around the VOPs using SVM based CV classifier [4] [8]. The main issues in spotting CV units in the proposed approach are location of VOPs with good accuracy and development of SVM based classifier capable of discriminating large number of CV classes.

2.1 Location of anchor points
Utterances of CV units consist of all or a subset of the following significant speech production events: closure, burst, aspiration, transition and vowel. The VOP is the instant at which the consonant part ends and the vowel part begins in a CV utterance. Since the vowel region is prominent in the signal due to its large amplitude characteristics and periodic excitation property, it is easy to locate this event compared to other speech production events. The information necessary for classification of CV units can be captured by processing a portion of the CV segment containing parts of the closure and vowel region, and all of the burst, aspiration, and transition regions. The closure, burst, and aspiration regions are present before the VOP. The transition and vowel regions are present after the VOP. Because every CV utterance has a VOP, the VOPs can be used as anchor points for CV spotting. This approach requires detection of VOPs in continuous speech with a good accuracy. The VOPs of all CV segments in a continuous speech utterance should be detected with minimum deviation. Since labelling will be done only for the segments around the VOPs detected, the effect of any VOP not being detected is that the CV segment around that VOP will not be recognised. Therefore it is important to minimise the number of missing errors by the VOP detection method. The effect of spurious VOPs being detected is that segments around them will also be given to the CV classifier for labelling.

In the method proposed in [9], a multilayer feedforward neural network (MLFFNN) model is trained to detect the VOPs by using the trends in the speech signal parameters at the VOPs. We consider AANN models for detection of VOPs [3]. A five layer AANN model, with compression layer in the middle has important properties suitable for distribution capturing, data compression, and extraction of higher order correlation tasks [10] [11]. We explore the distribution capturing of feature vectors by the AANN models to hypothesise the consonant and vowel regions and then detect VOPs in continuous speech. In Section 3.1, we describe the method used for VOP detection in continuous speech using AANN models.

2.2 Classifier for recognition of multilingual CV segments
Hidden Markov models (HMM) are used in most speech recognition systems. These models use maximum likelihood (ML) approach for training. The incre-
mental model optimization approach in ML framework simplifies the training process, but loses discriminative information in the process [12]. This is due to the fact that training data corresponding to other models are not considered during the optimization of parameters for a given model. Training by optimization over the entire pattern space gives better discriminative power to the models since the models now learn patterns that need to be discriminated. Multilayer feedforward neural network (MLFFNN) models and support vector machine (SVM) models are good at this type of learning since the training involves optimization over entire pattern space [3]. MLFFNN models have been shown to be suitable for pattern recognition tasks because of their ability to form complex decision surfaces. In order to obtain a better classification performance it is necessary to tune the design parameters such as structure of network, number of epochs, learning rate parameter and momentum. For better generalization, it is necessary to have large amount of training data. But arriving at optimal parameters for complex recognition problem using MLFFNN models is a difficult proportion. SVM models have attained prominence due to their inherent discriminative learning and generalization capabilities from the limited training data. These models learn the boundary regions between patterns belonging to two classes by mapping the input patterns into a higher dimensional space, and seeking a separating hyperplane so as to maximize its distance from the closest training examples. In the next section, we describe CV recognition system using SVM models for classifying the CV segments around the hypothesised VOPs.

3 System for spotting CV units

Speech database consisting of recordings of TV news bulletins in Tamil, Telugu and Hindi languages is used in our studies. A brief description of the speech corpus for these three languages is given in Table 1. We consider an approach for recognition of multilingual CV units in which the data for similar CV classes across the Indian languages are combined [4]. The similar classes from different languages are derived from Indian Language Transliteration (ITRANS) code [13]. The ITRANS code was chosen, as it uses the same symbol to represent the same type of sound units across the Indian languages. After combining 123, 138, and 103 classes from Tamil, Telugu and Hindi respectively, we get 260 unique classes. A summary of the database used for the development of multilingual system is given in the last column of Table 1. Each bulletin contains 10 to 15 minutes of speech from a single (male or female) speaker. The CV utterances in the database are segmented and labeled manually. The CV units have different frequencies of occurrence in the database. We consider a set of CV classes that have a frequency of occurrence greater than 50. Short-time analysis of the speech signal of the CV utterances is performed using frames of 20 msec duration with a shift of 5 msec. Each frame is represented by a parametric vector consisting of 12 mel-frequency cepstral coefficients (MFCC), energy, their first order derivatives and their second order derivatives [14]. Thus the dimension of each frame is 39. A multilingual system is developed for spotting CV units for the data of all the three languages.
3.1 System for detection of VOPs

A five layer AANN model to capture distribution of feature vectors is shown in Fig. 1. In this model the input and output layers have the same number of units, and all these units are linear. For each CV class, two AANN models (one corresponding to consonant and another to vowel regions) are developed. For training the AANN model corresponding to the consonant region, the fifth frame to the left of the manually marked VOP frame is selected from each of the training examples. For training the AANN model corresponding to the vowel region we consider the VOP frame and the fourth frame to the right of VOP frame. The model corresponding to a region of a CV class captures the distribution of feature vectors. The distribution is expected to be different for the consonant and vowel regions of a class. The distribution of feature vectors of a region is captured using a network structure 39L 60N 4N 60N 39L, where L refers to linear units and N refers to nonlinear units. The integer value indicates the number of units in that particular layer. The activation function for the nonlinear units is a hyperbolic tangent function. The network is trained using error backpropagation algorithm in pattern mode for 1000 epochs.

![Five layer AANN model](image)

Fig. 1. Five layer AANN model.

For detection of VOPs in continuous speech, each frame is given as input to the pairs of AANN models of all the CV classes. From the evidence available in the outputs of the models of a class, the hypothesised region of the frame is
obtained as the region of the model with higher evidence. The hypotheses from the models of different CV classes are used to assign the frame to the consonant or vowel region. In this way we obtain a sequence of region labels for the sequence of frames of the continuous speech utterance. VOP frames are identified as those frames, at which there is a change of labels from consonant to vowel. The block diagram of the system for detection of VOPs in continuous speech utterances is shown in Fig. 2.

**Fig. 2.** Block diagram of the system for detection of VOPs in continuous speech. $E_c(k)$ and $E_v(k)$ are the evidence obtained from consonant and vowel region models of $k^{th}$ class respectively. $H(k)$ is hypothesised region of the current frame by the models of class $k$. $H$ is the hypothesis of the current frame.

### 3.2 Classification system for recognition of multilingual CV units

SVM models are suitable for handling patterns of fixed dimension. For this purpose, a segment of fixed duration around the VOP that contains most of the information necessary for classification of CV utterances can be processed to derive a fixed dimension pattern. Portions of a CV utterance in the beginning and the end are not included in the fixed duration segment, since they may be affected by the coarticulation effects.

For fixed dimension representation of each CV utterance of the training data, we consider 65 msec around the VOP. Five overlapping frames are considered to the left of VOP and five to the right of VOP, with a shift of 5 msec. Thus, the pattern vector for each CV utterance is a 300-dimension vector formed by
concatenating the feature vectors of 10 successive frames. To reduce computations complexity, we propose nonlinear compression of the large dimension input pattern vectors using AANN models [15][11]. The block diagram of the system for recognition of multilingual CV units is shown in Fig. 3. It consists of three stages. In the first stage, the 300-dimension input pattern vectors \( \mathbf{x} \) are compressed to 60-dimension, using an AANN with structure 390L 585N 60N 585N 390L. These compressed pattern vectors are used to train the SVM classifier. One-against-the-rest approach is used for decomposition of the learning problem in \( n \)-class pattern recognition into several two-class learning problems [16]. SVM models are generated by assigning one model to each class, and training this model by considering data from all the three languages. An SVM is constructed for each class by discriminating that class against the remaining \( (n - 1) \) classes. The recognition system based on this approach consists of \( n \) number of SVMs. The set of training examples \( \{(x_i, k)\}_{i=1}^{N_k} \) consists of \( N_k \) number of examples belonging to \( k^{th} \) class, where the class label \( k \in \{1, 2, \ldots, n\} \). All the training examples are used to construct an SVM for a class. The SVM for the class \( k \) is constructed using a set of training examples and their desired outputs, \( \{(x_i, y_i)\}_{i=1}^{n} \). The examples with \( y_i = +1 \) are called positive examples, and those with \( y_i = -1 \) are called negative examples. An optimal hyperplane is constructed to separate positive examples from negative examples. The separating hyperplane (margin) is chosen in such a way as to maximize its distance from the closest training examples of different classes [5]. The support vectors are those data points that lie closest to the decision surface, and therefore the most difficult to classify. For a given pattern \( \mathbf{x} \) around the VOP, the evidence \( D_k(\mathbf{x}) \) is obtained from each of the SVMs. In the decision logic, the class label \( k \) associated with the SVM that gives maximum evidence is hypothesised as the class of the pattern \( \mathbf{x} \) representing the CV segment around VOP.

![Fig. 3. Block diagram of the multilingual CV recognition system for labelling region around the VOP.](image)

The block diagram of the integrated system for spotting multilingual CV units in continuous speech utterances is given in Fig 4. The speech signal is
given as input to the VOP detection module to locate VOPs in it. The short-time analysis is performed on 65 msec segment around each of the hypothesised VOPs to extract 390-dimensional MFCC based pattern vectors. This pattern vector is compressed to 60-dimensional using AANN compression network. The compressed pattern vector is given to the multilingual CV recognition system to hypothesise the CV class of the current segment. Thus a sequence of hypothesised CV units is obtained for the given speech utterance.

Fig. 4. Block diagram of the multilingual continuous speech recognition system based on spotting CV units.

4 Spotting CV units in continuous speech

For illustration, we consider a Tamil language speech utterance /kArgil pahudy-ilirundu UDuruwalkArarhaL/ consisting of 16 syllables (kA, rgil, pa, hu, di, yi, li, run, du, U, Du, ru, vāl, kA, rār, haL) whose waveform is shown in Fig. 5 (a). The hypothesised region labels using VOP detection system are shown in Fig. 5 (b). The label C corresponds to consonant region and V to vowel region. Using the procedure described in Section 3.1, the VOPs are detected. The hypothesised locations in terms of sample numbers (320, 720, 2440, 3760, 4800, 5560, 6200, 7480, 9480, 11120, 12080, 13240, 14560, 16960) are shown in Fig. 5 (c).

For comparison we consider manually marked VOP locations (280, 2360, 3800, 4920, 5480, 6320, 7400, 8200, 9440, 11160, 12080, 12520, 13200, 14520, 15840, 16960) shown in Fig. 5 (d).

It is seen that there are three VOPs (their sample numbers are indicated in boldface) that have been missed around the locations 8200, 12520, and 15840 corresponding to the syllables /ru/, /ru/, and /ra/, respectively. The VOP at location 720 is hypothesised as spurious VOP. For the segments around the hypothesised VOPs, the five alternatives hypothesised by the multilingual CV recognition system are given in Table 2. It is seen that for most of the segments the actual CV class of the segment is present among the alternatives. The correctly identified classes in the CV lattice are written in boldface. The segment around the hypothesised location 11120 has been hypothesised as /mU/, where as the actual syllable is /U/. This belongs to the case in which the vowel is in
the initial portion of word. Recognition of only vowels is not addressed in the current studies. All the classes hypothesised by the recognition system are of type CV.

We study the performance of the spotting approach for recognition of CV units for a large number of sentences in three Indian languages. For testing we consider 120, 120 and 60 sentences selected at random from 1416, 1348, and 630 sentences for Tamil, Telugu and Hindi languages, respectively. These 300 sentences from different languages consist of a total number of 3924 syllable-like units corresponding to 1580, 1648 and 696 actual VOPs from sentences of Tamil, Telugu and Hindi languages, respectively. These VOPs have been marked manually. For each sentence the hypothesised VOPs are determined by the AANN method explained in Section 3.1. The VOPs that are detected with a deviation upto 25 msec are about 68.62% and there are about 6.21% of spurious VOPs. About 74.63% of the CV segments have been correctly recognised in five alternatives by spotting the CV segments around the detected VOPs.

5 Summary and conclusions

In this paper, we have addressed the issues in consonant-vowel (CV) spotting based approach for multilingual speech recognition. The approach is based on using the vowel onset points (VOPs) as anchor points and then classifying the segments around VOPs using a classifier. Autoassociative neural network (AANN) models are used for detecting VOPs in continuous speech. The methods for minimising the number of missing VOPs have to be explored. We use support vector machine (SVM) based classifier for recognition of CV segments around the hypothesised VOPs. The hypothesised CV sequence can be processed to
perform word-level matching and sentence-level matching to recognise complete sentences.

References


<table>
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<tr>
<th>VOP locations</th>
<th>Lattice of hypothesised CVs</th>
<th>Actual</th>
<th>Position</th>
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<tbody>
<tr>
<td>280</td>
<td>nA kA nA la shu kAr</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>290</td>
<td>nA kA nA la pa ga</td>
<td>1</td>
<td></td>
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<tr>
<td>300</td>
<td>nA kA nA pa sa pa</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>310</td>
<td>nA kA nA mu vu pu mu</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>320</td>
<td>nA kA nA ni zi ni yi</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>330</td>
<td>nA kA nA ru ja ru li</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>340</td>
<td>VOP Missed run</td>
<td></td>
<td></td>
</tr>
<tr>
<td>350</td>
<td>dh Ru lA ME kA ku</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>360</td>
<td>Nu kA Na p0 kA kA</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>370</td>
<td>VOP Missed ru</td>
<td></td>
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</tr>
<tr>
<td>380</td>
<td>va kA la li VA val</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>390</td>
<td>kA ga cha za kA kA</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>400</td>
<td>VOP Missed kar</td>
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<td>ha kA la ga sa haL</td>
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