ABSTRACT

Phone level localization of mis-articulation is a key requirement for an automatic articulation error assessment system. A robust phone segmentation technique is essential to aid in real-time assessment of phone level mis-articulations of speech, wherein the audio is recorded on mobile phones or tablets. This is a non-standard recording set-up with little control over the quality of recording. We propose a novel post processing technique to aid Spectral Transition Measure (STM)-based phone segmentation under noisy conditions such as environment noise and clipping, commonly present during a mobile phone recording. A comparison of the performance of our approach and phone segmentation using traditional MFCC and PLPCC speech features for Gaussian noise and clipping is shown. The proposed approach was validated on TIMIT and Hindi speech corpus and was used to compute phone boundaries for a set of speech, recorded simultaneously on three devices - a laptop, a stationary placed tablet and a handheld mobile phone, to simulate different audio qualities in a real-time non-standard recording environment. F-ratio was the metric used to compute the accuracy in phone boundary marking. Experimental results show an improvement of 7% for TIMIT and 10% for Hindi data over the baseline approach. Similar results were seen for the set of three of recordings collected in-house.

Index Terms— Spectral Transition Measure, Clipping, Noise, F-score

1. INTRODUCTION

Phonetic segmentation is the process of breaking down a given speech utterance into its basic units, namely phones. Accurate and robust phonetic segmentation is a key requirement for an automatic mis-articulation assessment system, wherein the spoken speech could be from a patient undergoing speech language therapy or a student wishing to learn a new language. Feedback needs to be given based on the accuracy of pronunciation of each phone, thus making phone level localization of mis-articulation essential. Several techniques have been proposed for phonetic segmentation, popular ones being, Automatic Speech Recognition (ASR) based, wavelet analysis based and Spectral Transition Measure (STM) based. In [1][2][3] authors, address the accuracy of the phonetic segmentation using a two-step approach, wherein the initial estimate is obtained using an ASR and the boundaries are further refined using specific boundary level acoustic models, approach based on regression tree and on acoustic-phonetic knowledge, respectively. Authors use similar approach in [4], wherein the boundaries were improved using powerful statistical models conditioned on phonetic context and duration features. However, any ASR based method is dependent on the availability and quality of speech corpus in a particular language. Phonetic boundaries have been computed using several speech parameterizations such as Mel Frequency Cepstral Coefficients (MFCC), Perceptual Linear Prediction Cepstral Coefficients (PLPCC), RelAtive SpecTrAl (RASTA)-based PLPCC, wavelet-based parameters. In [5] authors use Fourier-based and wavelet-based parameterization for a Viterbi time-alignment based phonetic segmentation. A phonetic segmentation algorithm based on power fluctuations of the wavelet spectrum for a speech signal has been proposed in [6]. Discrete Wavelet transform (DWT), its power spectrum and its derivatives have been used to achieve phonetic segmentation. Phonetic segmentation and classification using wavelet based transforms was used to enhance frequencies adaptively in hearing aids by authors in [7]. Maximum marginal clustering (MMC), a kernel method has been applied for unsupervised phonetic segmentation [8]. Phonetic boundaries are detected using a two-layered support vector machine (SVM)-based system using frequency synchrony and average signal levels computed using a biomimetic model of the human auditory processing [9]. These techniques have been reported to perform well on clean speech.

However, speech based mobile applications such as Siri, are gaining popularity and we envision that a robust mechanism for phonetic segmentation of recordings conducted in such non-standard set-ups are valuable to building speech based applications on mobile phones. Specifically, our objective is to assess mis-articulations in disordered speech at phone level and provide instant feedback to the user for corrective action through hand-held devices such as mobile phones or tablets. However, mobile phone or tablet record-
ings are perpetuated with environment noise and clipping. Phonetic segmentation using traditional methods and speech parameters alone will not provide the levels of accuracy required for such a task. Spectral Transition Measure is closely correlated with phonetic boundaries [10] and hence can be exploited to automatically obtain phonetic boundaries in a language independent manner. STM based methods have also been recently used to analyze the effectiveness of Perceptual linear prediction (PLP) based features in speech synthesis [11]. We propose a novel post processing mechanism for Spectral Transition Measure (STM) based phonetic segmentation, through which accuracies for noisy speech (environmental noise and clipping) was improved, which is the main contribution of this paper.

The organization of the paper is as follows: Section 2 describes the STM-based phonetic segmentation approach and its limitations . Section 3 discusses the distortions in speech recorded using handheld devices such as mobile phones and tablets. Section 5 describes the design of our experiments for evaluating the proposed technique. Section 6 discusses the results from discusses the evaluation results. Finally,Section 7 concludes the paper along with directions for future work.

2. PHONETIC SEGMENTATION ALGORITHM

In literature various automatic phonetic segmentation algorithms are reported. However, in our work we have used STM algorithm for automatic phonetic segmentation [12]. For a given speech signal we compute STM is as follows,

\[ f = [\bar{f}_1, \bar{f}_2, ..., \bar{f}_m] \]

where \( \bar{f}_i \) is spectral feature vectors of D-dimension and \( m \) is total number of frames for a given speech signal. Than, Equation 2 defined the rate of spectral feature with \( \bar{a} = [a_1, a_2, ..., a_D] \).

\[ \bar{a}(m) = \frac{\sum_{n=-L}^{L} n \bar{a}(n)}{\sum_{n=-L}^{L} n^2} \] (1)

\[ STM(m) = \frac{\sum \bar{a}(m)^2}{D} \] (2)

STM is defined as mean-squared value of spectral rate using Equation 2. The locations of local maxima obtained in the STM contour indicate spectral transition or a phone boundary. The STM algorithm for phonetic segmentation was originally proposed using MFCC features [12, 10]. In [11], authors have achieved improvement over the state-of-the-art using PLPCC features for automatic phonetic segmentation. In our work we are using PLPCC base STM as our baseline algorithm. Figure 1 depicts the STM contour corresponding to a clean speech utterance wherein phone boundaries are captured using peak-picking.

Fig. 1: (a) Original signal (‘Don’t Ask Me’ from TIMIT) with corresponding manually marked boundaries (red lines) and automatic segmented boundaries (black lines) (b) STM contour using baseline algorithm.

2.1. Limitations of the state-of-the-art

The limitations of the baseline algorithms for clean speech signal are:

- Spurious boundaries are introduced in the silence part of the speech signal, due to the high sensitivity of the STM computation algorithm which is marked as label S in Figure 1.

- Over-segmentation in the vowel regions due to the large duration of vowels which marked as label V Figure 1.

Apart from clean speech, signal distortion like clipping and noise further degrade the performance of the baseline algorithm. As shown in Figure 2 because of clipping we get spurious boundaries marked as label C. Similarly in Figure 3 because of noise we got spurious boundaries marked as label N.

3. DISTORTIONS IN SPEECH FROM NON-STANDARD RECORDING ENVIRONMENTS

Assessment of mis-articulations in disordered speech in real-time is done under non-standard environments, using handheld devices such as mobile phones or tablets. However, it was observed that the performance of algorithms designed for clean speech are degraded on non-standard recordings speech due to (a) clipping - depends on the distance between the user and the mobile device, (b) environment noise We discuss how the presence of these distortions impacts phonetic segmentation.
3.1. The influence of clipping

Clipping is a distortion that occurs when an audio signal level exceeds the dynamic range of the recording device. The only way to avoid clipping is by maintaining the recording device at a fixed distance and an uniform volume, which is not possible in a non-standard environment. It has been reported in literature that presence of clipping in speech reduces the speech recognition performance \[13\]. Clipping causes the appearance of additional frequencies in the spectral representation of the speech signal. Clearly (see Figure 2), clipping changes the speech signal and subsequently reflecting in the STM contour. Small additional peaks occur in the regions of clipped speech of the STM contour. The proposed post processing technique addresses this issue.

3.2. The influence of environment noise

Noise is an additional unwanted component in the signal. It is extremely difficult even for experts to find out the true position of phonetic boundaries in noisy speech signal. From Figure 3 it is evident that presence of noise change speech signal and hence the STM contour.

These distortions have been catered by proposed post processing technique.

4. PROPOSED POST-PROCESSING TECHNIQUE

This section discusses the novel post-processing method for phonetic segmentation. Traditional methods have reported good accuracy in terms of precision and recall for a 20 ms tolerance. However, over-segmentation is a cause of concern when applied to our specific application of misarticulation assessment of disordered speech. Further, the over-segmentation problem intensifies in the presence of noise (environmental and clipping). We propose a post processing mechanism wherein the STM contour peaks that are considered as phonetic boundary are selected based on a threshold determined dynamically for each STM contour unlike the boundary correction methods that employ experimentally determined threshold \[10\].

Median of the STM contour was found to be more suitable to be used as a threshold \(\tau_M\) for robust phonetic segmentation.

\[
STM(m) = \begin{cases} 
STM(m), & \text{if } STM(m) > \tau_M \\
\tau_M, & \text{otherwise}
\end{cases}
\]  

(3)

The median threshold \(\tau_M\), also catered to identification and elimination of spurious boundaries inserted within a vowel due to the large duration of the vowel region. In Section 4.1 we will discussed the proposed robust phonetic segmentation algorithm.

4.1. Algorithm

1. Read the speech file and corresponding manual transcription
2. Extract D = 12 dimension PLPCC feature for each 30 ms frame with 20 ms overlap
3. Compute rate of change of spectral features \(\Bar{a}\) using Equation [1] with \(I=2\)
4. Compute mean squared value (STM) using Equation (2) and get the STM contour
5. Estimate the meaningful threshold on STM contour
6. Modify the STM using Equation (3)
7. Peak peaking on STM contour and estimate the boundaries
8. Compare Estimate boundaries and manual boundaries using 20 ms tolerance interval
9. Compute Precision, Recall and F-score

In next section we will discussed about experimental setup for testing proposed algorithm.

5. EXPERIMENTAL SETUP

The proposed post processing algorithm was validated on noisy data simulated using clean TIMIT and Hindi speech corpus. The performance of the algorithm was compared with (a) clean data (b) with different levels of clipping simulated on clean data (c) different degrees of noise introduced into the original speech signal.

5.1. Data Preparation

5.1.1. Validation data
To validate language independence of the proposed algorithm, we experimented on two different language databases.

- TIMIT American English acoustic-phonetic corpus - This database[14] contains utterances from 630 speakers, each reading 10 sentences. This entire database contains 2,34,925 between-phone boundaries manually determined by experts. These boundaries do not include the boundaries placed at the beginning and end of the sentence.

- Hindi acoustic-phonetic speech corpus - This speech corpus [15] contains a total of 1000 Hindi sentences along with their phone level transcription. Speech was recorded as 16 bit PCM, mono at 8 kHz. 10 sentences were spoken by each of the 100 speakers from 11 major linguistic regions of India. This entire database contains 55,104 between-phone boundaries manually marked.

5.1.2. Test data
The approach was also tested on data recorded in Hindi on three different devices simultaneously. 18 sentences from 7 speakers was recorded using a setup as shown in the Figure 4. Speech on laptop was recorded using a close talking microphone, on mobile phone, a hands-free microphone was held in the hand by the user and the tablet was placed stationarily on the table. Speech was recorded in wave format at 16 kHz. We consider the laptop recording as clean data in this set. Figure 5 shows time domain speech signal recorded on three different devices laptop, tablet and mobile with corresponding manually marked phone boundaries. The recorded test data having very less silence/pause region as compare to validation database. In addition to this, is observed from Figure 5 that laptop recorded signal is clean without any distortion, mobile recorded signal is clipped and tablet recorded signal having background noise. This data contains 3997 phonetic segments for each recording device.

5.2. Simulated data for validation
We simulate clipping using following transformation.

\[ x_c(n) = \begin{cases} 
  x(n), & \text{if } x(n) < \tau \\
  \tau \cdot \text{sgn}(x[n]), & \text{if } x(n) \geq \tau 
\end{cases} \tag{4} \]

where \( x_c(n) \) is clipped signal of original signal \( x(n) \) and \( \tau \) is decided based on amount of clipping percentage we introduced for a given speech signal. Clipping percentage was varied from 10 to 90 steps of 20. For simulated noise standard additive white Gaussian noise with varying SNR level from between 0 db to 20 db was used. Both the baseline approach and the novel approach were validated on the above data.
5.3. Performance measures

To measure the performance of proposed approach, we use standard precision-recall measures.

- **Precision** - It is defined as the score of total number of boundaries estimated in given 20 ms tolerance interval to the total number detected boundaries.

- **Recall** - It is defined as the score of total the number of boundaries estimated in given tolerance interval to the total number ground truth boundaries. Recall is same as %Accuracy.

- **F-score** - It is defined as,
  \[ F-score = \frac{2 \times Precision \times Recall}{Precision + Recall} \]

The Range of these measure varies from 0% to 100%.

6. EXPERIMENTAL RESULTS AND ANALYSIS

PLPCC speech parameterization was used for both baseline and novel approach. A comparison of the performance of both the algorithms are as shown in Table 1 for both TIMIT and Hindi speech data. We got 7% and 10% improvement over the baseline algorithm for TIMIT and Hindi data respectively. It is evident from the Table that proposed post processing method performs better as compared to the baseline algorithm. Figure 6 shows the results of proposed post-processing method on simulated clipped and noisy data. It is evident from the figure that proposed method performs better compared to baseline algorithm for distorted data as well. For up to 50% clipping and for SNR greater than 5 (db), proposed method gives good results.

| Database | Hindi | TIMIT |
|----------|-------|-------|
| Baseline | 68.76 | 70.72 |
| Proposed | 79.22 | 77.84 |

Similar experiments were carried out on test data mentioned in Section 5. The F-score for the three recordings are as shown in the Table 2 with different tolerance interval.

| Tolerance (ms) | Laptop | Mobile | Tablet |
|---------------|--------|--------|--------|
| 20            | 55.48  | 58.25  | 56.35  |
| 30            | 66.12  | 69.04  | 68.48  |
| 40            | 71.48  | 74.34  | 75.60  |

7. CONCLUSION

Phone level localization of mis-articulation is a key requirement for an automatic articulation error assessment system. Robust phonetic segmentation techniques become imperative for such a system. In this work, a novel post processing technique was presented for phone segmentation under noisy conditions such as environment noise and clipping, commonly present during a mobile phone recording. The proposed approach was validated on TIMIT and Hindi speech corpus where the results show an improvement of 7% for TIMIT and 10% for Hindi data over the baseline approach. For both MFCC and PLPCC features, with PLPCC feature providing a better performance.

![Wave file for three different recording medium with corresponding manual segment boundaries.](image)

![Fig. 5: Wave file for three different recording medium with corresponding manual segment boundaries.](image)

![Fig. 6: (a) % F-score for TIMIT speech corpus with clipping (b) % F-score for Hindi speech corpus with clipping (c) % F-score for TIMIT speech corpus with noise (d) % F-score for Hindi speech corpus with noise.](image)

![Table 1: % F-score comparison between baseline and proposed techniques for clean speech](image)

![Table 2: % F-score for speech signals recorded under non-standard conditions using proposed method](image)
better segmentation. Similar results were seen for a set of speech, recorded simultaneously on three devices - a laptop, a stationarily placed tablet and a handheld mobile phone, to simulate different audio qualities in a real-time non-standard recording environment.

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