ANALYSIS OF NATURAL AND SYNTHETIC SPEECH USING FUJISAKI MODEL

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ABSTRACT
Text-to-speech (TTS) synthesis systems are being advanced to achieve naturalness and intelligibility in synthetic speech. Unit selection-based synthesis (USS) and Hidden Markov Model-based text-to-speech synthesis systems (HTS) are recent techniques in this area. USS-based synthetic speech is known to be natural (due to concatenation of natural speech sound units). On the other hand, HTS-based speech is not as natural in perception as USS-based synthetic speech. Due to speech synthesis technologies, voice biometers systems may face threats due to impostor attacks. Thus, it is important to study the differences that exist between natural and synthetic speech. In this context, we investigate the effectiveness of parameters of Fujisaki model for capturing Fundamental frequency ($F_0$) contour variations in natural and synthetic speech. $F_0$ contour of speech contains linguistic and non-linguistic information. Experimental results on several utterances from Gujarati (a low resourced language) demonstrate the effectiveness of phrase and accent components to analyze the difference between these two speeches. Variability in phrase and accent components suggests that synthetic speech differs in terms of prosodic information in excitation source as compared to natural speech. These findings may assist to distinguish these two speeches and provide an aid to alleviate impostor attacks.

Index Terms-Fujisaki model, accent, phrase, synthetic speech.

1. INTRODUCTION
Text-to-Speech (TTS) synthesis techniques have remarkably developed in the past decade. One of these techniques includes development of unit selection-based synthesis (USS) using Festival framework [1] (which requires large recorded data and its transcription). USS synthesized speech is natural in perception and intelligible if the transcription is accurate enough. Another technique is statistical parametric speech synthesis based on Hidden Markov Model (HMM)-based TTS synthesis systems (HTS) [2], [3], [4]). Attempts to improve quality of speech synthesis techniques are being vulnerable for speaker recognition and verification systems due to the problem of impostor attack. Due to less training data required, HTS-based attacks are more common than the USS-based attacks. This occurs in scenarios where it is needed to authenticate if a particular speech is uttered by a genuine speaker. Other attacks may be due to mimicking (twins), replay, face under cover and voice transformation, etc. Here, we look into attacks due to state-of-the-art USS and HTS synthesis systems. In this paper, we propose to analyze natural vs. synthetic speech by exploiting prosodic information in excitation source during speech production.

Fundamental frequency ($F_0$) carries linguistic and non-linguistic information [5]. It carries information such as the speaker’s identity, emotion, mood, etc. $F_0$ contour is known to be the result of movement of intrinsic muscles in the larynx [5]-[6]. The model representing these movements is well known as the Fujisaki model or the command-response model. It represents $F_0$ contour in terms of the phrase and accent parameters as a result of the translation and rotation motion of the cricoids muscles, respectively [7]. Earlier in [8]-[9] features like the pitch pattern and its variability were used as source features to detect synthetic speech. Other than source-based features, in [10] relative phase shift (RPS) was used to detect synthetic speech. Here, we use variations in $F_0$ contour (in terms of Fujisaki model parameters) of natural and synthesised speech to study the source-based discriminative features between the two speeches. In mimic speech, an imitator tries to vary his/her $F_0$ contour so that the shape of the $F_0$ contour matches with the target speakers $F_0$ contour [11]. However, speech synthesis technologies are not so human-like to perform such close matching to the $F_0$ contour of the natural speech. In other words, the natural speech is uttered with appropriate breaks and accent variations, which is not the case for synthetic speech. Therefore, we investigate the Fujisaki model parameters of natural and synthetic speech for discriminating these two speeches.

2. THE FUJISAKI MODEL
The Fujisaki model assumes the $F_0$ contour in log-domain as the superposition of two mutually independent contributions that occurs due to the independent movement of the thyroid cartilage and muscular reaction times [5]-[7]. Fujisaki model works for various languages (i.e., it gives good synthetic model contours) [6]. Here, we use Fujisaki model for Gujarati (a low resourced Indian language).
2.1 The Model

Fujisaki model is a superposition of phrase components \(y_p\) and accent components \(y_a\). The two contributions are superimposed with a constant value \(F_0\) (i.e., minimum value of the speaker’s \(F_0\), which is known to be speaker-specific) to give a particular model generated \(F_0\) contour as in Fig. 1.

![Fig. 1. Functional command response model for the process of generating \(F_0\) contour.](image)

The phrase and accent components are impulse response and step response of critically damped 2nd order linear system that is excited by Dirac impulses called phrase commands \((x_p)\) and rectangular pulses called accent commands \((x_a)\), respectively [5]. The output of phrase control mechanism \(y_p\) is characterized by the following impulse response,

\[ h_p(t) = \alpha e^{-\alpha t}u(t), \]

where \(\alpha \in [2, 4] s^{-1}\) is its natural angular frequency. On the other hand, the output of the accent control mechanism \(y_a\) is characterized by following step response,

\[ g_a(t) = (1 - (1 + \beta t)e^{\beta t})u(t), \]

where \(\beta \in [19, 21] s^{-1}\) is its natural angular frequency. The total \(F_0\) contour of the utterance can be expressed as,

\[ y(t) = \ln(F_0(t)) - \ln(F_a) = y_p(t) + y_a(t), \]

\[ y(t) = \sum_{i=1}^{N_p} A_{p,i} h_p(t - t_{p,i}) \quad \text{and} \quad y_a(t) = \sum_{i=1}^{N_a} A_{a,i} g_a(t - t_{a,i}), \]

where \(N_p\) and \(N_a\) are the number of phrase and accent events; \(A_{p,i}\) and \(A_{a,i}\) are the magnitude and timing of the \(i^{th}\) phrase command; \(t_{p,i}\) and \(t_{a,i}\) are the magnitude, onset time and the end time of \(i^{th}\) accent command. In Fig. 1, the nonlinear system for glottal airflow effects has been ignored [5].

2.2 Extraction of Model Parameters

2.2.1 \(F_0\) Extraction

Extracting prosodic events from speech requires estimating \(F_0\) contour of speech. Here, we use the zero frequency filtering (ZFF) method to estimate the \(F_0\) contour [12]. The epoch locations, i.e., the glottal closure instants (GCIs) are obtained from the negative-to-positive zero-crossings of the zero frequency filtered signal. Thereafter, the \(F_0\) contour is obtained from the GCI locations. Fujisaki model requires a continuous contour and it deals with macroprosodoy only. Hence, two tasks are performed before modeling the \(F_0\) contour; (1) intermediate values for unvoiced speech regions and short pauses are interpolated in the \(F_0\) contour, (2) microprosodic variations due to individual speech sounds units (such as plosives, fricatives, etc.) are smoothed out. Here, a linear fit is used during interpolation and then the \(F_0\) contour has been smoothed prior to parameter estimation. Fig. 2 shows the \(F_0\) contour extracted from ZFF algorithm where the unvoiced regions are interpolated with a linear fit.

![Fig. 2. (a) Speech from TIMIT database [13] (16 kHz), (b) original \(F_0\) contour (black) and linear interpolated \(F_0\) contour (green).](image)

2.2.2 Phrase and Accent Command Extraction

The processed \(F_0\) contour is then used to estimate the phrase and accent events. The detection of phrase events or phrase boundaries is based upon the work reported in [14]. The \(F_0\) contour is lowpass filtered and the negative-to-positive transition of the derivative of the filtered \(F_0\) contour is taken as phrase boundaries. The strength of the phrase boundary was estimated by slope of the line at the negative-to-positive crossings. Accent commands parameter extraction is based on the work carried out in [15]. The procedure is to detect the largest maximum and the smallest minimum for each interval where the sign of the derivative of \(F_0\) remains same. A pair of maximum and minimum corresponds to the onset and the offset of an accent command. An example of the Fujisaki parameters extracted from a speech utterance at 16 kHz is shown in Fig. 3. It is observed that model generated contour approximates smooth version of original \(F_0\) contour.

![Fig. 3. (a) Speech signal, (b) phrase commands (blue) and phrase components (dashed), (c) accent commands (blue) and accent components (dashed) and (d) original \(F_0\) contour and model generated \(F_0\) contour (dashed).](image)

3. GENERATION OF SYNTHETIC VOICES

The USS system is built using Festival framework [1], [16]. Since Indian languages are generally syllable-timed [17], we use syllable as the speech sound unit. Text optimization was carried to obtain 95 % syllable coverage [16]. The speaker selection was done as in [18] and the recorded data was labeled using semiautomatic DONLabel labeling tool that
uses group delay-based techniques for labeling at syllable-level [19]. The labeled data was manually aligned by trained professionals. The Gujarati USS systems (male and female) were built on 8 hours of speech data with an average mean opinion score (MOS) of around 3.3. HMM-based synthesis framework gives a general setup for context modeling and is easily adapted to other languages [20]. For Gujarati the phonemic representation consists of 49 phonemes, broadly classified into SIL (i.e., silence), 36 consonants and 12 vowels [21]. HTS systems were built on 5 hours of speech data with average MOS of 3 (male) and 2.7 (female).

4. SPECTROGRAPHIC ANALYSIS

For experiments, 100 male and 100 female utterances were used each for natural, USS and HTS system. Same text material is used for both natural and synthetic speech. Fig. 4 shows the spectrogram for natural speech, USS and HTS-based synthesized speech for the same utterance. The spectrogram of USS-based synthesized speech is similar to the natural speech in terms of speaker characteristics. However, there are breaks in the spectrogram representing discontinuity in the formant contour (dotted oval showing abruptness due to concatenation). These breaks may also occur in natural speech however, the frequency of their occurrences in USS-based speech is relatively more due to concatenation of speech sound units. The spectrogram of HTS-based speech shows loss in intelligibility and the formant structure do not appear to be preserved in HTS-based speech (dotted squares).

We quantify the difference in various spectrograms by the Itakura–Saito (IS) distance measure. It measures perceptual difference between an original spectrum \( P(o) \) and its approximation \( \hat{P}(o) \). We consider synthetic speech to be an approximation to the natural speech. The utterances were time-aligned using Dynamic Time Warping (DTW) [22] and linear prediction coefficients (LPC) were extracted from the speech signal for every 20 ms speech frame with a frame shift of 10 ms for computation of IS distance, given by [23],

\[
D_{IS}(P(o), \hat{P}(o)) = \frac{1}{N} \sum_{n=0}^{N-1} \log \left( \frac{P(o_n)}{\hat{P}(o_n)} \right)^{-1},
\]

where \( N \) is the number of speech frames. Table 1 shows that the IS distance is relatively less between natural and USS speech as compared to HTS speech because IS distance measures spectral characteristics reliant on the size and shape of the vocal tract of the individual.

Table 1. Average IS distance between natural and synthetic speech over 100 male and 100 female utterances.

<table>
<thead>
<tr>
<th>Dn</th>
<th>USS</th>
<th>HTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>11.675754</td>
<td>14.994685</td>
</tr>
<tr>
<td>Female</td>
<td>9.2565341</td>
<td>18.448603</td>
</tr>
</tbody>
</table>

5. ANALYSIS BY FUJISAKI MODEL PARAMETERS

The model generated \( F_0 \) contour in log-domain is a superposition of phrase component \( (y_p) \), accent component \( (y_a) \) and \( F_0 \). The following sub-section shows variations of these parameters for natural and synthetic speeches.

5.1 Minimum Value of \( F_0 \) Contour \( (F_0) \)

In the representation of Fujisaki model, \( F_0 \) is the baseline value of \( F_0 \) contour. It is a constant term \( c_F(T_m/\sigma)^{1/2} \), where \( c_F \) is a constant inversely proportional to size of the membrane, \( T_m \) indicates the static tension applied to the vocal fold and \( \sigma \) is the density per unit area of the membrane [7]. \( F_0 \) is approximated as a constant as long as the speaker maintains same speaking style and emotional state [6]. \( F_0 \) for female should be higher than male for natural, USS and HTS voices (as in Table 2). For USS, the speech sound units are concatenated using units from the same speaker. Therefore, mean value of their \( F_0 \) is nearly same to natural. However, as the units are concatenated from several sessions of recording, there exists more variability in the \( F_0 \) (more standard deviation \( (sd) \)). More the professional artists are consistent in recording, lesser would be the variation in \( F_0 \). For HTS, the mean \( F_0 \) will be close to the natural speech if naturalness in HTS speech is persevered. However, other direct inferences for \( sd \) could not be drawn; hence, phrase and accents components are used for further analysis.

5.2 Phrase Commands and Phrase Components

The instant when the cricoid muscles undergo a translation motion, an impulse is generated corresponding to phrase breaks which occur naturally during speech production. Such prosodic breaks are not more prominent in synthetic speech. Fig. 5 shows the number of breaks in the natural and the synthetic speeches. In USS, silences are introduced in synthetic speech as per the text punctuations, whereas during natural speech production, prosody is automatically generated as per the nature of the utterance, context, etc. Therefore, USS synthesized speech is expected to have less...
Table 2. The distribution (in terms of the mean and standard deviation (sd)) for 100 male and 100 female utterances (USS and HTS) of the minimum value of $F_2$ contour ($F_2$), the phrase components ($\gamma$) and the accent components ($\nu$).

<table>
<thead>
<tr>
<th>Parameters of model</th>
<th>Natural Male</th>
<th>Natural Female</th>
<th>USS Male</th>
<th>USS Female</th>
<th>HTS Male</th>
<th>HTS Female</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F_2$</td>
<td>64.79</td>
<td>60.454</td>
<td>123.12</td>
<td>19.374</td>
<td>67.73</td>
<td>8.7885</td>
</tr>
<tr>
<td>Mean</td>
<td>sd</td>
<td>Mean</td>
<td>sd</td>
<td>Mean</td>
<td>sd</td>
<td>Mean</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.1158</td>
<td>0.1055</td>
<td>0.3894</td>
<td>0.2722</td>
<td>0.1481</td>
<td>0.1082</td>
</tr>
<tr>
<td>Mean</td>
<td>sd</td>
<td>Mean</td>
<td>sd</td>
<td>Mean</td>
<td>sd</td>
<td>Mean</td>
</tr>
<tr>
<td>$\nu$</td>
<td>0.3396</td>
<td>0.2306</td>
<td>0.3753</td>
<td>0.2811</td>
<td>0.2797</td>
<td>0.1993</td>
</tr>
<tr>
<td>Mean</td>
<td>sd</td>
<td>Mean</td>
<td>sd</td>
<td>Mean</td>
<td>sd</td>
<td>Mean</td>
</tr>
</tbody>
</table>

or equivalent number of phrase breaks as compared to the natural speech as seen in Fig. 5. For HTS male and female, the number of phrase breaks increases. Next, impulses due to phrase commands are passed through 2nd order phrase control mechanism, to produce the phrase components. USS synthesized speech have similar means and sd for phrase components to that of natural utterances (as in Table 2). In HTS, for the number of phrase breaks was more. However, their strength was less due to the fact that these breaks were due to phrase pauses decided from text and not due actual change in translational motion of the cricoid muscles. Hence, mean value of phrase component is less.

Fig. 5. Number of phrase breaks in natural, USS and HTS speech.

5.3 Accent Commands and Accent Components

The accent parameters of the Fujisaki model capture the variations in the speech which includes the stress that is applied to a particular word, syllable, etc. Especially for interrogative and exclamatory types of sentences, the accent parameters vary significantly. In case of USS speech, due to concatenation, the natural variation due to stress on syllable, word etc. may not always be present. Hence, the synthetic speech is monotonous in listening and this brings a possibility for the accent commands and components to vary less than natural speech. Thus, for USS synthesized speech, the mean and sd of the accent components was less than the natural speeches (as shown in Table 2). In case of HTS, any uniform pattern for the accent parameters was not found for either male or female.

5.4 Statistical Analysis of Results

The scatter plots for 100 USS and HTS synthesized voices formed by the mean of accent and phrase components are shown in Fig. 6. The clusters for USS and natural speech are different in size and shape than HTS and natural speech. In particular, clusters for USS synthesized and natural speech are found to be more overlapping and it is difficult to identify a boundary for these two classes. On the other hand, for HTS speech (especially female voice), the two classes are easily separable. Thus, the female voice in HTS lacks relatively the prosodic features as that of the natural voice.

To know the difference in distribution of the parameters for the natural and synthetic voices, we performed the Student’s $t$-test and investigate if the two sets of synthetic voices are significantly different from natural. It is seen from Table 3 that the null hypothesis for all the synthetic voices is rejected with very less probability (<than 0.0001) in most cases. Hence, the natural and synthetic systems (USS and HTS) have diverse means, which is effective while training statistical models like GMM, etc. This shows that the phrase and accent parameters could prove a good set of features to distinguish natural and synthetic.

Fig. 6. Clusters of accent and phrase components. (a) natural vs. USS (male), (b) natural vs. HTS (male), (c) natural vs. USS (female) and (d) natural vs. HTS (female).

<table>
<thead>
<tr>
<th>System</th>
<th>USS</th>
<th>Accent</th>
<th>HTS</th>
<th>Accent</th>
</tr>
</thead>
<tbody>
<tr>
<td>$M$</td>
<td>&lt;0.0001</td>
<td>&lt;0.0001</td>
<td>&lt;0.0001</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>$F$</td>
<td>&lt;0.0001</td>
<td>0.018</td>
<td>&lt;0.0001</td>
<td>0.0002</td>
</tr>
</tbody>
</table>

6. SUMMARY AND CONCLUSIONS

This paper presented an analysis of natural vs. synthetic speech using phrase and accent parameters of the Fujisaki model. For both USS and HTS, it was observed that phrase command could serve as an important feature to distinguish between natural and synthetic speech. For HTS speech, phrase components could be effective. Results of $t$-test show that the null hypothesis is rejected in all cases, which is effective while training statistical models on large dataset. Thus, our future research will be directed towards exploring these excitation source features for classification problem and apply these features to alleviate voice biometric attack.
7. REFERENCES


