International Journal of Innovation Sciences and Research
Vol.7, No, 11, pp.1257-1263, November, 2018
Available online at *http://www.ijisr.com*

RESEARCH ARTICLE

A ROBUST FREQUENCY-DOMAIN METHOD FOR ESTIMATION OF INTENDED FUNDAMENTAL FREQUENCY IN VOICE ANALYSIS

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Accepted 17th October 2018; Published Online 30th November 2018

ABSTRACT

This paper presents a new algorithm to detect the intended fundamental frequency (F0) in human voice. Accurate detection of F0 is the first step when computing multiple important voice analyses, such as harmonics to noise ratio (HNR), frequency variations within utterances and voice harmonics. These, in turn, allow voice recognition and identification, which have wide applications from voice pathology diagnosis to automatic answering algorithms and robotic voice commanded systems. The proposed algorithm explicitly incorporates the following voice-specific characteristics in frequency domain: presence of harmonics in human voice, continuity of intended F0 over small time intervals and presence of intensity reinforcement in F0. The latter allows the algorithm to remain robust when analyzing voices that present subharmonic (pathological) components.

Key words: Human Voice, Signal Processing, Formants, F0 Estimation, Spectrogram.

INTRODUCTION

Voiced and unvoiced excitations constitute the two basic types of speech sounds (Martínez *et al.,* 2012). In the case of voiced excitations, or vocalized voice, the voice signal presents periodic oscillations of a certain frequency, called fundamental frequency (F0). The F0 and its multiples (harmonics) determine the formant structure and the aural perception of a given sound (Mitev, 2003). Human voice, however, may present pathological characteristics that are not handled correctly by fundamental frequency estimation algorithms, such as presence of subharmonics, as shown in Figure 1. Computation of F0 allows estimation of harmonics to noise ratio from the spectrogram due to harmonics being integer multiples of F0. It can also be used to narrow the search region for formants in the spectrogram. Applications range from speaker identification (Daqrouq and Tutunji, 2015) and speech recognition (Irino *et al.,* 2012) to voice command recognition (with cepstral coefficients, shown by (Principi *et al.,* 2015)). F0 estimation using the proposed algorithm allows more accurate harmonics to noise (HNR) computation in the presence of subharmonics, which makes HNR a more reliable tool for voice-controlled applications and preliminary clinical voice diagnosis. In robotics, it also allows development of voice-controlled systems which use F0 and vowels as control inputs as long as operators do not have severe voice pathologies. An underwater robot, for example, could have vowel [a] command to rise and [u] to dive, with speed controlled by F0. This work is structured as follows: Section 1.1 briefly describes biological filters and specific characteristics of human voice. Section 1.2 describes related work on F0 estimation. Section 2 describes the proposed algorithm and provides details on how the presence of harmonics and reinforcement in F0 are used to enhance F0 estimation. Section 3 describes the Saarbruecken database (Putzer and Barry, 2007) and visualization of the data in phonetics softwares Praat (Boersma and Weenink, 2013) and Prati Canto, the computer program where the proposed algorithm is implemented. Finally, Section 5 presents conclusions, limitations of the proposed algorithm and future work.

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Biological Filters in Human Voice

When analyzing human voices, a very important aspect are filters, which constitute a selective frequency transmission system, which allows energy through some frequencies and not others. Biological, usually nonlinear, band-pass filters make this possible (Maxfield and Palaparthi, 2016). The spectrogram is a tridimensional arrangement that shows time, frequency and intensity. Multiple horizontal lines (as shown in Figure 1) correspond to voice harmonics. Vocal folds vibration frequency corresponds to the perceived F0 in normal voices. Voice formants reveal frequency regions of greater energy concentration, as shows Figure 2. These are peaks of greater amplitude in the sound spectre and are inherent to a certain configuration adopted by the vocal tract during vowel speech. When a word is spoken, formants are associated with natural resonance frequencies of the vocal tract, and depend on tongue positioning relative to inner structures and to lip movement. The system can be approximated by tube with one closed extremity (larynx) and one open (lips), modified by tongue, lips and pharynx movement. The resonance which occurs in the cavities of this tube is called formant. Vowels are characterized by three main formants: formant 1 (pharynx), formant 2 (oral cavity) and formant 3 (lips). Formant 1 depends on how open the vowel sound is and how much tongue displacement is needed in the vertical plane. Formant 2 depends on horizontal displacement of the tongue. Formant 3 is influenced by lip rounding and is essential in differentiating vowels. These frequency reinforcements are extremely useful to identify F0 and their existence is explicitly used in the proposed F0 estimation algorithm.

Related Work: The estimation of signal frequencies is relevant in multiple fields, such as operation of electric power systems, damping controllers, determination of speech intelligibility (Marchesan *et al.,* 2013; Hill *et al.,* 2016; Chen *et al.,* 2016). There are three main methods to estimate F0: autoregression in time domain, cepstral methods and frequency domain methods (Manfredi *et al.,* 2000). Autoregressive models offer reliable and robust estimation suitable for many applications, with the added advantage of being capable of fitting mathematical models, such as harmonic and chirp, that do not need to assume that voiced segments are constant in small intervals (Nrholm *et al.,* 2016). However the algorithm is sensitive to the presence of subharmonics, as are cepstral methods. Bootstrap based estimation methods are viable and accurate when the assumption that the frequency of the signal is random holds (Hernández *et al.,* 2017). Frequency domain methods are very useful for voice analyses in view of their ability to identify reinforced frequencies. Expectation maximization methods applied to short-time Fourier transform of sound signals has been used for real-time detection of melody and bass in CD recordings (Goto *et al.,* 2000). Principal component analysis based on the spectrogram is a viable technique to separate singing voice from other sounds (Ikemiya and Itoyama, *et al.,* 2016). Specific techniques have been developed for diplophonic voices in frequency domain, but they require F0 tracking and was not designed to be robust in the presence of sub harmonics. The algorithm described herein is implemented in frequency domain because this is the domain where specialists usually perform voice analsys, using spectrograms, such as the one shown in Figure 3. The approach is based on the statistical F0 estimation algorithm proposed by (Chu and Alwan, 2012), adding the requirements that harmonics are a multiple of F0 and that F0 must have a minimum intensity (or else they cannot correspont to vocal fold vibration frequency). Explicit use of human voice characteristics lead to a robust implementation for intended F0 estimation, as described in Section 2. In particular, the main contributions are the explicit consideration that harmonics are integer multiples of F0 and direct assessment of signal power contained in each frequency, which allows for rejection of F0 candidates whose power level is too low to correspond to vocal folds vibration frequency, which is the intended F0 in human voice. In recent works, harmonic enhancement is proposed to improve pitch estimation (Wu *et al.,* 2016). Even in these works, however, proper estimation of F0 is necessary in order to compute harmonics to noise ratio.

Algorithm Description: Figure 4 presents an overview of the proposed algorithm. First, the acoustic signal is decomposed into its spectral components. Then, peak picking determines candidate F0 values, following steps proposed by (Chu *et al.,* 2012). Explicit, non-statistical analyses are then made: the frequency closest to being the GCD of frequencies containing high intensity is a lower bound to F0. Finally, F0 value is required to have a minimum intensity.

Local DFT maxima and F0 candidates: Ordinarily, F0 estimation in frequency domain by peak picking is very sensitive to noise and local maxima in intensity. As stated in Section 1.2, the proposed algorithm explicitly takes into consideration specific characteristics of human voice:

- Lowest possible F0: F0 cannot be lower than 60 Hz, both because this region is outside of human voice range and to reject interference of electric supply;
- Presence of formants: human voice has reinforced intensity at specific frequencies, depending on the vocalized sound being produced. Parabolic interpolation allows accurate identification of the reinforced frequencies (Mitev *et al.,* 2003) and identification of F0 candidates;
- Presence of harmonics: human voice has harmonics and formants due to resonance mechanisms. Approximation of F0 as the greatest common divisor (GCD) of reinforced frequencies allows establishing an upper bound to F0;
- Reinforcement of intended F0: excluding severe pathological cases, during vocalized speech, the intended F0 has reinforced intensity. Computation of the first local maximum of the discrete Fourier transform allows identification of a lower bound for F0.

The proposed algorithm performs analyses in frequency domain. The discrete Fourier transform (DFT) is used to this end. Let y be the raw wave data. Y is its DFT computed using 2048 points after Hanning window is applied. DFT is applied to y according to Equation 1, using the Fast Fourier Transform (FFT) algorithm.

$$Y_k = \sum_{n=0}^{N-1} y_n \cdot exp(-2\pi kn/N), k \in \mathbb{Z} \quad (1)$$

Multiple 2048 point windows are displayed sequentially in a spectrogram, as shown in Figure 3. Once the power spectrum absY = 20log10|Y | is computed in the region, a mean filter is computed and stored in absY Smooth, F0 candidates are estimated using peak picking in absY Smooth with parabolic interpolation.

. **Result:** Output frequency-intensity pairs corresponding to local maxima in power spectrum absY
Initialize frequency-intensity $FreqIntens$ pairs as empty list;
Smooth absY: for each element k, $absYSmooth[k] = \frac{1}{3}(absY[k-1] + absY[k] + absY[k+1])$;
foreach *element k in absYSmooth* **do**
    if $absYSmooth[k] \geq absYSmooth[k-1] \& absYSmooth[k] \geq absYSmooth[k+1]$ **then**
        Retrieve frequencies corresponding to each intensity;
        Find local maximum using 3-point parabolic interpolation;
        Add interpolated frequency-intensity pair to output $FreqIntens$;
    end
end

Algorithm 1: Peak picking in power spectrum

Peak picking is implemented as follows. Let x0 = $freq_{k-1}$, x1 = $freq_k$, x2 = $freq_{k+1}$ be the frequencies (in Hz) associated with y0 = absY $Smooth_{k-1}$, y1 = absY $Smooth_k$, y2 = absY $Smooth_{k+1}$. If absY Smooth[k] >= absY Smooth[k−1] and absY Smooth[k] >= absY Smooth[k + 1], then the frequency-intensity pair is computed according to Equations 2 and 3:

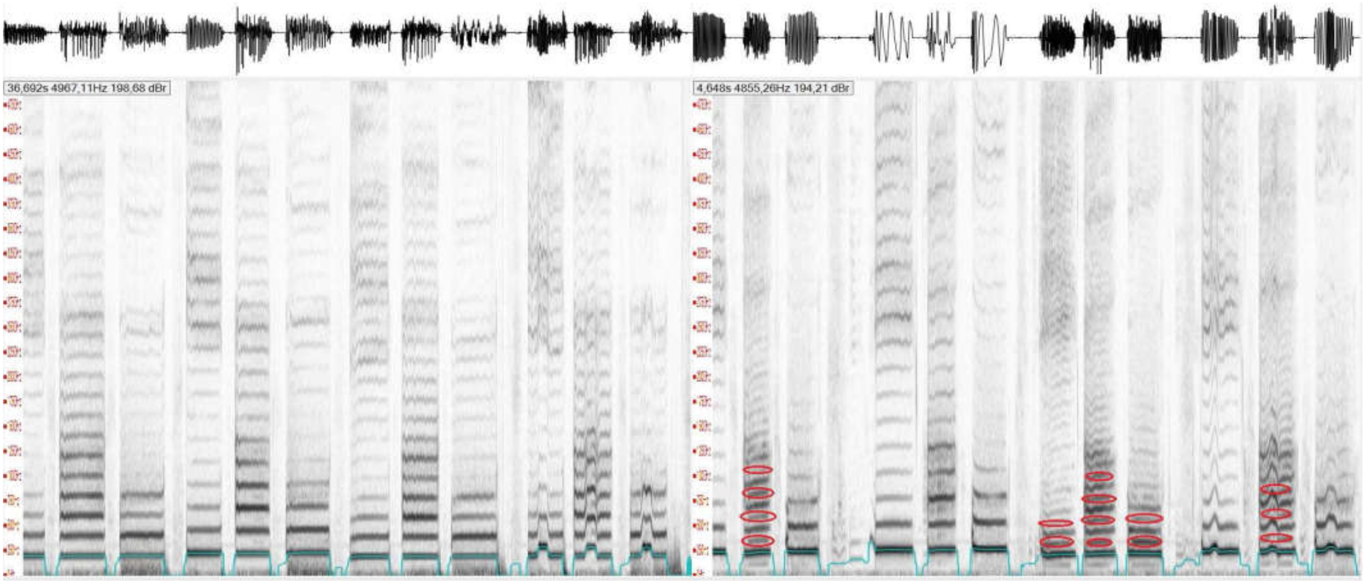

Fig. 1. Voice spectrogram comparison (F0 highlighted). Left: female normal voice. Right: pathological female voice. Note the presence of subharmonics (marked with red circles)

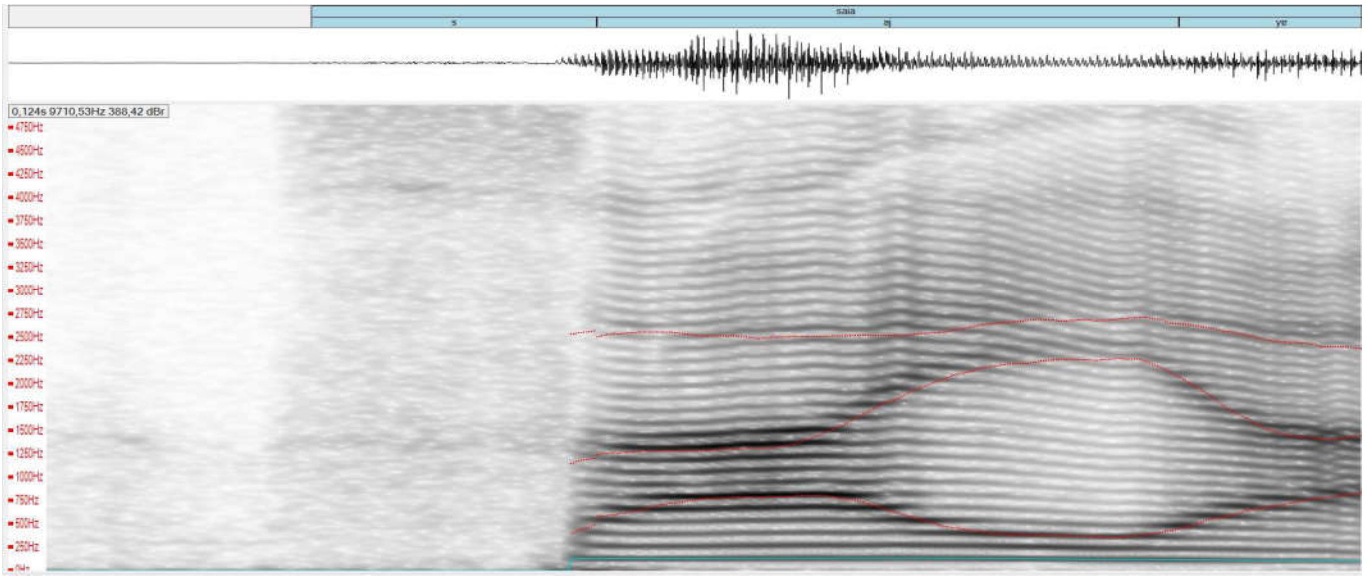

Fig. 2. Diphthongs explicited in word ”saia” (phonetic notation in the picture), with voice formants highlighted in red.

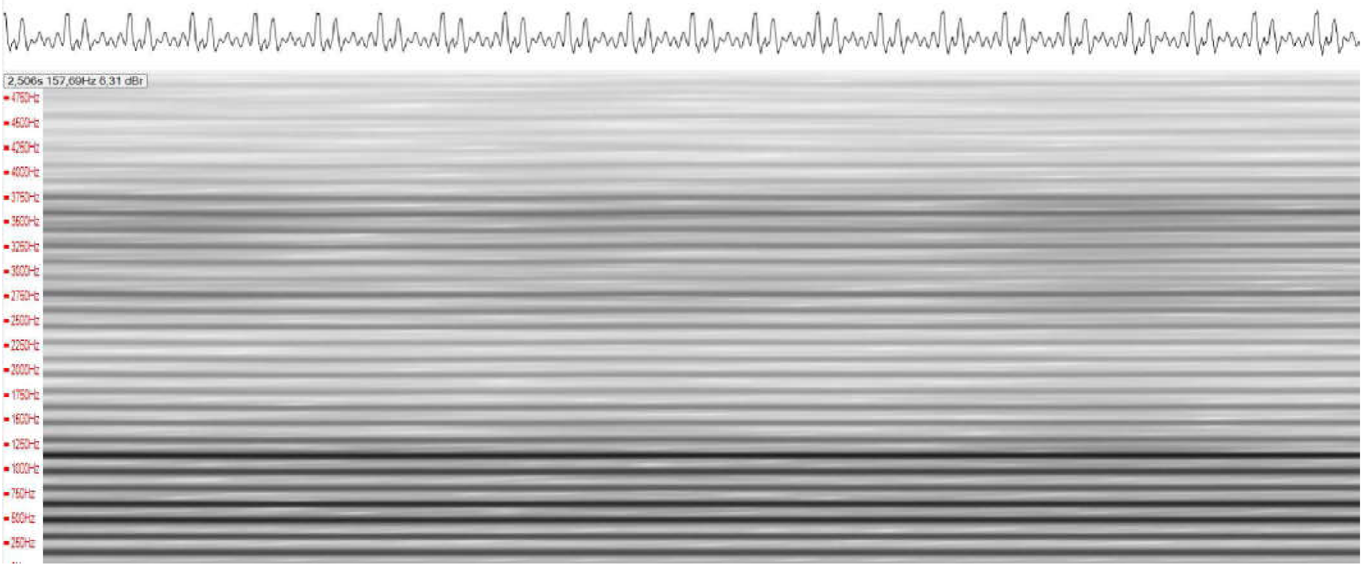

Fig. 3. Voice spectrogram. Top: voice wave form. Bottom: power spectra of sequential regions (spectrogram)

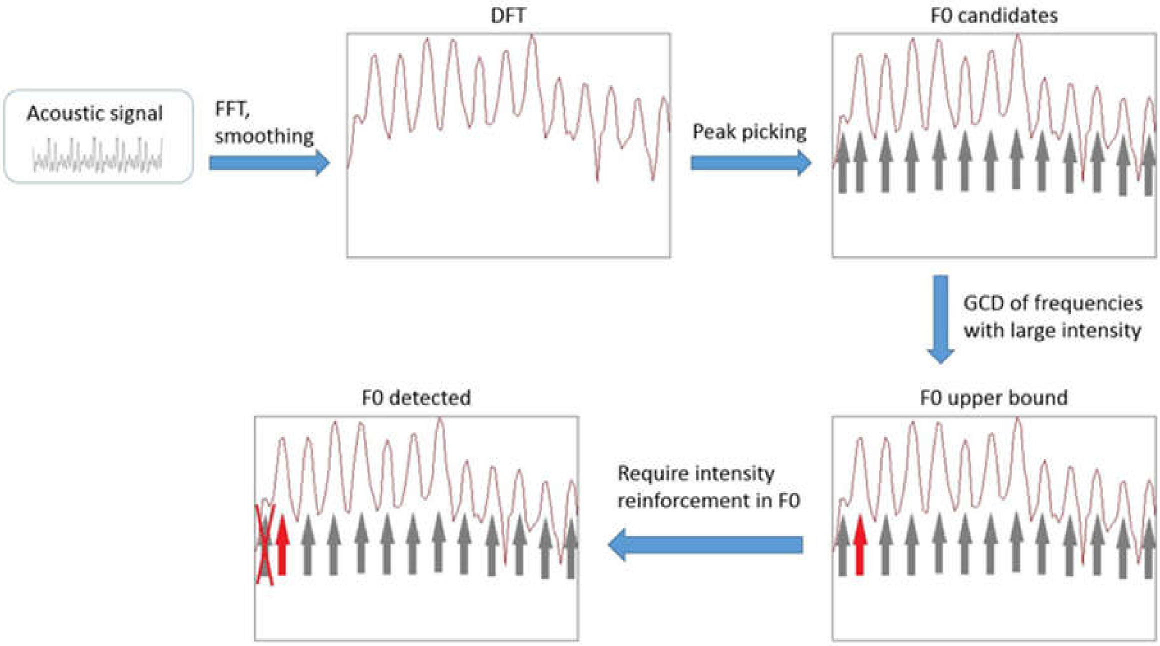

Fig. 4. Intended F0 identification algorithm overview

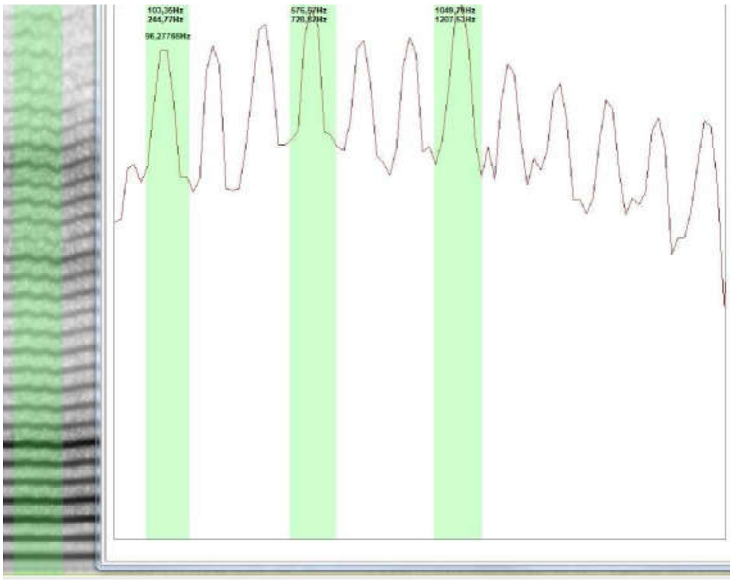

Fig. 5. Voice spectrum peaks. Left: spectrogram. Right: power spectrum corresponding to selected region in green.

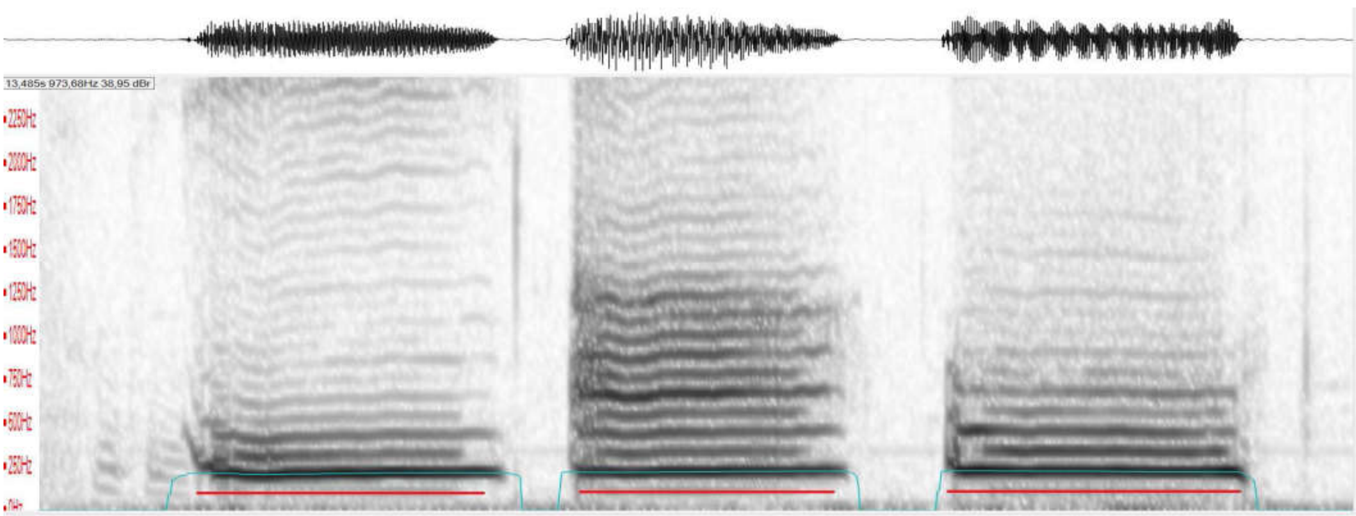

Fig. 6. Pathological voice presenting subharmonics. Blue line shows intended F0; red line shows "mathematical" F0, not intended by speaker

Table 1. Performance results - % of correct F0 estimation

File	Praat	Proposed Algorithm
Word 6	85.2%	97.5%
Word 7	100%	100%
Word 8	79.5%	96.5%

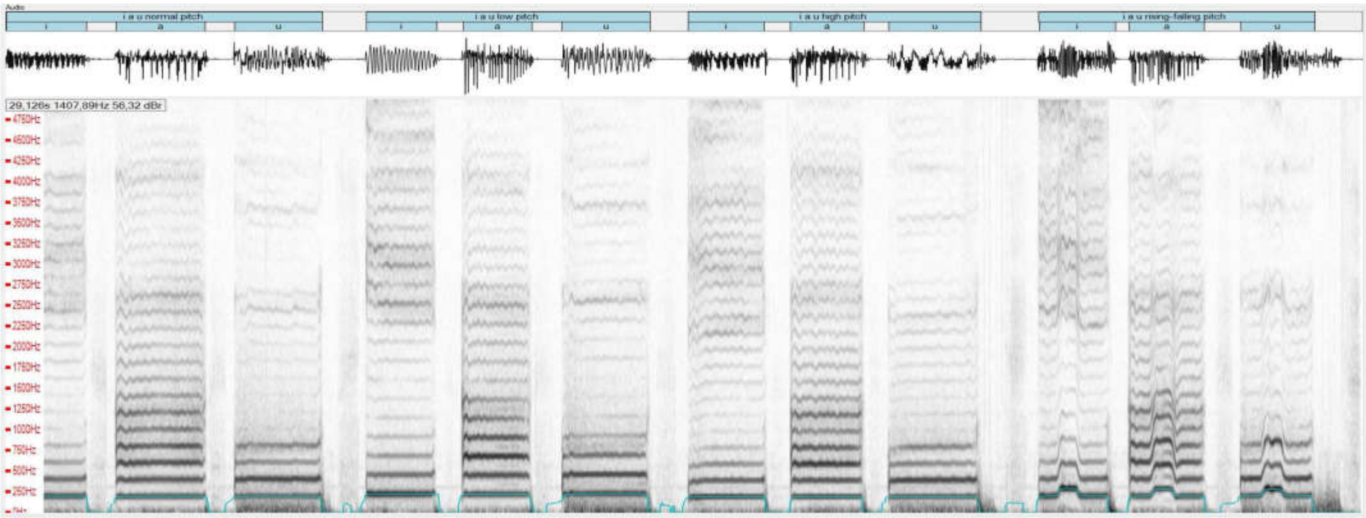

Fig. 7. Sample recording from the Saarbruecken voice database

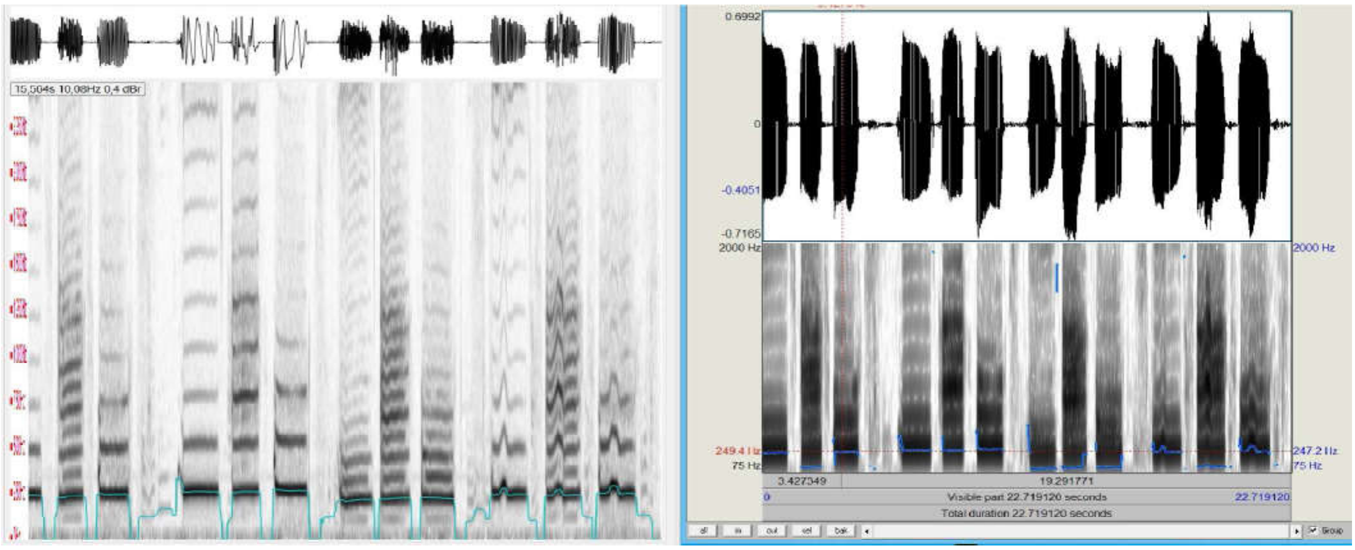

Fig. 8. Performance comparison when voice presents subharmonics. Left: proposed algorithm. Right: Praat. Note that intended F0 is incorrectly identified using the proposed algorithm even when subharmonics are present

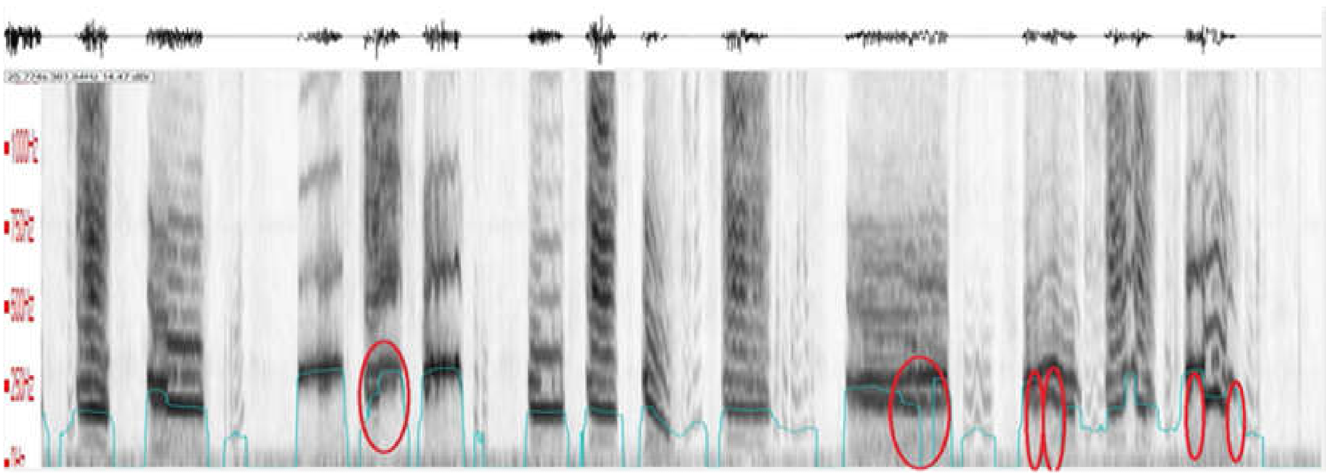

Fig. 9. Errors in intended F0 identification in the proposed algorithm

$$
\begin{aligned}
invD &= \frac{1}{(x_0-x_1)*(x_0-x_2)*(x_1-x_2)}\\
a &= (x_0(y_2-y_1)+x_1(y_0-y_2)+\\
&\quad +x_2(y_1-y_0))\cdot invD\\
b &= (x_0^2(y_1-y_2)+x_1^2(y2-y_0)+\\
&\quad +x_2^2(y_0-y_1))\cdot invD\\
c &= (x_0^2(x_1y_2-x_2y_1)+x_1^2(x_2y_0-x_0y_2)+\\
&\quad +x_2^2(y_1x_0-y_0x_1))\cdot invD\\
inv2A &= \frac{1}{2a}
\end{aligned} \tag{2}
$$

$$
\begin{aligned}
interpIntens &= c-\frac{b^2}{2\cdot inv2A}\\
interpFreq &= -b\cdot inv2A
\end{aligned} \tag{3}
$$

Were harmonics not reinforced or voice structure not to be used, picking the highest intensity element of FreqIntens would return F0, which is not the case. Picking the first local maximum does not work either, as shown in Figure 5. Note that the first peak corresponds to noise and that the desired F0, at approximately 120Hz, does not have the highest intensity. The presence of harmonics allows establishing an upper bound to F0, as described in subsection 2.2.

Harmonics, F0 reinforcement and Continuity

Human voice presents harmonics, integer multiples of F0 to a degree that can be exploited in the identification algorithm. In fact, harmonics (and formants) are so prominent that they are intentionally tuned and they define styles of singing (Sundberg, 2013; Sundberg and Thaln, 2015). In the proposed algorithm, a lower bound to F0 is computed as the minimum of the GCD of frequency-intensity pairs (Freq Intens), provided that the intensity is at least 14% of the maximum peak intensity, as long as the intensity of F0 itself is at least 5% of the maximum peak intensity. These values were manually tuned using audio recordings and samples from the voice database. Whenever the F0 candidate has too low intensity, its frequency is doubled - this is necessary to account for the presence of subharmonics in pathological voices. In a strict analysis, while a pathological voice containing subharmonics has its physical F0 at a given frequency f, the intended F0 is 2f. In this sense, voices cannot be treated as ordinary signals as the perceptual auditory component points to humans that the perceptual answer is F0 = 2f. In the spectrogram, this result is clearly shown in Figure 6. The red line marks F0 if the signal were not to be treated as human voice. The blue line highlights the intended F0. Note that errors in this computation would lead to wrong computation of harmonics to noise rations because the pathological subharmonics would be added to the harmonic component. Note that there is no reinforcement in frequency f, which indicates presence of pathology in the voice and indicates to the human ear that it is not the intended F0. The last step in F0 detection is post processing by computing median filter over an interval of 20 ms, which is a duration short enough for the speech to be considered constant.

Experimental Data

The voice database consists of two recordings per person: vowels [i, a, u] produced at normal, high and low pitch followed by vowels [i, a, u] with rising-falling pitch and the sentence ”Guten Morgen, wie geht es Ihnen?” (”Good morning, how are you?”) (Putzer and Barry, 2007). Voices are classified in the database as ”Normal” or identified with the pathology. In this work, all comparisons used the vowel recordings, because they allow better manual identification of the intended F0. Figure 7 shows a sample spectrogram (database voice 10). Most files contain 9 sustained segments followed by 9 approximately constant segments with rising-falling pitch, while some may contain more or less regions due to patient misunderstanding of what sound should be produced. Since there are normal voice frequency variations (jitter) (Goy *et al.,* 2013; Teixeira, 2014) and relevant errors in F0 identification return twice or half of its value, results within 10 Hz of manual verification are considered correct for the purposes of the analyses in Section 4. This value is robust enough for proper harmonic to noise estimation, which takes into account a neighborhood of the harmonics (Wu *et al.,* 2016). F0 identification has to be correct in the entire interval.

Tests and Results

A total of 520 sustained vowels from 30 files were analyzed using Praat as reference software (Boersma, 2013), the proposed algorithm and manual check. Praat is a free scientific computer software for analysis of speech in phonetics designed in the University of Amsterdam. Tests were performed using the freely available Saarbruecken Voice Database (Putzer and Barry, 2007), using audio files recorded from normal voices and pathological voices uttered by individuals who had cyste in their vocal folds. Performance results were as shown in Table 1. Typical errors in Praat algorithm, as expected, occur when subharmonics are present in the voice, as shown in Figure 8. Table 1 shows that the proposed algorithm significantly outperforms Praat when identifying F0 in pathological voices. F0 computed in Praat would be correct for an ordinary periodic signal, since all reinforced frequencies are, indeed, multiples of F0/2 and not multiples of the intended F0. However, in the context of voice analysis, this result is not acceptable. The vibration of the vocal folds generates reinforcement in F0 and, in Figure 6, for example, it would mean that a female adult voice is being emitted with F0 approximately equal to 100 Hz, which visual and auditory perception clearly indicate is not true in that particular case. The proposed algorithm fails when the voice pathology is very severe, containing subharmonics and extremely low harmonic to noise ratio. It is hard even to manually detect the intended F0, as shows Figure 9.

Conclusion

The proposed algorithm, implemented in frequency domain, can robustly identify the intended fundamental frequency of human voice even in the presence of subharmonics. It explicitly incorporates the following human voice characteristics: harmonics, F0 continuity and F0 reinforcement. Incorporating these features allows robust F0 estimation when the speaker does not have a severe voice pathology. Out of 520 sustained vowels obtained from the Saarbruecken Voice Database, F0 estimation is robust exceptin cases of severe pathology (97.5% of the total - 100% correct in normal voices and 96.5% correct in pathological voices). This is a significant improvement over Praat algorithm when voice pathologies are present (79.5% correct F0 estimation). Example applications for the algorithm include robotic voice-controlled systems using sustained vowels and preliminary clinical voice evaluation. Future work will be conducted to further investigate voice segments with very low harmonics to noise ratio and perform preliminary detection if the voice has severe pathology.

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