Source-filter Separation of Speech Signal in the Phase Domain

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Abstract

Deconvolution of the speech excitation (source) and vocal tract (filter) components through log-magnitude spectral processing is well-established and has led to the well-known cepstral features used in a multitude of speech processing tasks. This paper presents a novel source-filter decomposition based on processing in the phase domain. We show that separation between source and filter in the log-magnitude spectra is far from perfect, leading to loss of vital vocal tract information. It is demonstrated that the same task can be better performed by trend and fluctuation analysis of the phase spectrum of the minimum-phase component of speech, which can be computed via the Hilbert transform. Trend and fluctuation can be separated through low-pass filtering of the phase, using additivity of vocal tract and source in the phase domain. This results in separated signals which have a clear relation to the vocal tract and excitation components. The effectiveness of the method is put to test in a speech recognition task. The vocal tract component extracted in this way is used as the basis of a feature extraction algorithm for speech recognition on the Aurora-2 database. The recognition results shows up to 8.5% absolute improvement in comparison with MFCC features on average (0-20dB).

Index Terms: Speech phase spectrum, Source-filter decomposition, Hilbert transform, phase wrapping, minimum-phase component, Trend/Fluctuation analysis

1. Introduction

Phase spectrum of the speech signal has a very complicated behaviour. Its shape is noise-like and lacking in any meaningful trend or extremum points making it hard to model or interpret. Further, there are several studies that suggest it is unimportant from a perceptual point of view [1–4]. Although there are notable works that have exploited the phase [5–20], it is still a common practice to discard this spectrum after the Fourier analysis. Experimental studies have lacked a fundamental mathematical foundation such that would allow measurement of the information encoded by the phase spectrum. Useful reviews about the phase spectrum may be found in [21], [22] and [23].

In the case of the magnitude spectrum, the source-filter model is commonly employed to decompose the speech signal into its fundamental elements, i.e. the vocal tract (filter) and the excitation (source). The theory of such deconvolution based on cepstral (log-magnitude) processing is well-established and most speech processing methods make use of it in some way [24, 25]. However, in the case of the phase spectrum there is no algorithm for direct phase modelling to facilitate such decomposition, despite the fact that convolution in the time domain is equivalent to addition in the phase domain, which should potentially be useful for carrying out deconvolution. So, developing an algorithm for direct phase modelling to facilitate such decomposition is well-established and has led to the well-known cepstral features used in a multitude of speech processing tasks. This paper presents a novel source-filter decomposition based on processing in the phase domain. We show that separation between source and filter in the log-magnitude spectra is far from perfect, leading to loss of vital vocal tract information. It is demonstrated that the same task can be better performed by trend and fluctuation analysis of the phase spectrum of the minimum-phase component of speech, which can be computed via the Hilbert transform. Trend and fluctuation can be separated through low-pass filtering of the phase, using additivity of vocal tract and source in the phase domain. This results in separated signals which have a clear relation to the vocal tract and excitation components. The effectiveness of the method is put to test in a speech recognition task. The vocal tract component extracted in this way is used as the basis of a feature extraction algorithm for speech recognition on the Aurora-2 database. The recognition results shows up to 8.5% absolute improvement in comparison with MFCC features on average (0-20dB).

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In this paper, we present a novel method for source-filter modelling which enables the blind deconvolution of the speech using purely phase-based processing. This model provides insight into the way in which information is encoded in the phase spectrum and sheds light on the behaviour of the phase across the spectrum. The capability of the model to follow the temporal evolution of the vocal tract configuration and the excitation component will be demonstrated and discussed. In addition, we propose a parametrization method to demonstrate the efficacy of the suggested method in a speech recognition task.

The rest of this paper is structured as follows. Section 2 reviews the main issues with the phase spectrum-based analysis and modelling. In Section 3 the proposed method is introduced and investigated from different aspects. Section 4 presents the feature extraction process and noise-robust speech recognition results. Section 5 concludes the paper.

2. Properties of the phase spectrum

In speech processing, the magnitude spectrum plays the major role because of its harmony with our understanding of the physical characteristics of the speech production system and its benign behaviour from the mathematical standpoint. In particular, source (fundamental frequency) and filter (formant frequencies) elements, as the building blocks of the speech signal, can be obtained straightforwardly by decomposition in the cepstral domain. As in the cepstral domain, these two components are also additive in the phase domain. However, signal processing through phase manipulation is overwhelmingly difficult because of phase wrapping. This phenomenon is due to the atan2(...) function and gives the phase spectrum a chaotic shape, lacking any meaningful trend or extremum points. As a result, direct interpretation and modelling of this spectrum becomes extremely complicated. To produce a more understandable representation of the phase, researchers resort to working with its derivative, i.e. the group delay function (GDF).

2.1. Group Delay Function

Most of the phase-related works in speech processing are based on the GDF, \( \tau_X(\omega) \), which is defined as follows

\[
\tau_X(\omega) = -\frac{d}{d\omega} \arg[X(\omega)] = -Im\{\frac{d}{d\omega} \log(X(\omega))\} \tag{1}
\]

where \( \arg[\cdot] \) and \( Im\{\cdot\} \) denote the unwrapped (continuous) phase and imaginary part and \( \omega \) is angular frequency. Phase unwrapping is not straightforward [26] but the GDF can be computed while avoiding this issue by utilizing real and imaginary parts,

\[
\tau_X(\omega) = \frac{X_{re}(\omega)Y_{re}(\omega) + X_{im}(\omega)Y_{im}(\omega)}{|X(\omega)|^2} \tag{2}
\]
where $Y(\omega)$ is the Fourier transform of $nx[n]$ and the $Re$ subscript denotes the real part.

2.1.1. Pros and cons of working with GDF

There are several benefits of working with the GDF. First, under certain conditions, it has a relatively clear behaviour and resembles the magnitude spectrum. The second advantage is additivity, which means if two signals are convolved in the time domain their GDFs will be added. Third, it has a high frequency resolution, i.e. it is able to resolve closely located peaks in the frequency domain.

However, on the negative side, when the magnitude spectrum (denominator of Eq. (2)) gets close to zero, the GDF becomes very spiky and this will highly limit its usefulness. In the case of speech signals, the excitation component gives rise to the GDF spikiness, namely modified GDF (MODGDF) [12, 14, 32, 33]. Despite the relative success of these methods in tackling the aforementioned problem and returning an estimate of the vocal tract configuration, none of them provides insight into the way in which the source and filter components interact nor how such information is encoded in the phase spectrum. Therefore, our goal, i.e. source-filter modelling in the phase domain, is to compute $\arg[X_{VT}(\omega)]$ and $\arg[X_{EVT}(\omega)]$. To do so, first we need to compute the minimum-phase component of the $X(\omega)$, namely $X_{MinPh}(\omega)$.

2.1.3. Shortcoming of the Solutions

By suppressing the excitation element, these methods can not be successfully employed in applications where this component is of some significance. However, the more important issue with the GDF is that although the GDFs of the source and filter components are additive, decomposing the speech into these two parts through GDF-based processing is problematic in principle. This point will be explained in Section 3.3.2 but its direct implication is that the additive property of the GDF for doing deconvolution becomes practically ineffective.

3. Phase Spectrum Modelling

3.1. Preliminary

Speech is a mixed-phase signal [34] owing to its complex cepstrum being neither causal nor anticausal [24]; hence it can be decomposed into two complementary components, namely minimum-phase (MinPh), $X_{MinPh}(\omega)$, and all-pass (AllP), $X_{AllP}(\omega)$,

$$X(\omega) = |X(\omega)|e^{i\arg[X(\omega)]} = X_{MinPh}(\omega).X_{AllP}(\omega) \quad (3)$$

$$\begin{cases} |X(\omega)| = |X_{MinPh}(\omega)| \\ \arg[X(\omega)] = \arg[X_{MinPh}(\omega)] + \arg[X_{AllP}(\omega)] \end{cases} \quad (4)$$

As seen, the magnitude spectrum is only related to the MinPh part of the speech whereas the phase spectrum is linked to both the MinPh and AllP components. Since both vocal tract ($X_{VT}(\omega)$) and excitation ($X_{EVT}(\omega)$) elements manifest themselves in the magnitude spectrum, the minimum-phase component can be expressed as follows

$$\begin{cases} |X_{MinPh}(\omega)| = |X_{VT}(\omega)|.|X_{EVT}(\omega)| \\ \arg[X_{MinPh}(\omega)] = \arg[X_{VT}(\omega)] + \arg[X_{EVT}(\omega)]. \end{cases} \quad (5)$$

3.2. Computing the minimum-phase component

For recovering the minimum-phase component of a mixed-phase signal two approaches can be considered, parametric and non-parametric. In the parametric case, the $z$-transform of the sequence should be expressed in a rational form and all the poles and zeros which are located outside the unit circle are reflected inside. This method is not practical since the $z$-transform of an autoregressive-moving-average model is not available in practice. On the other hand, the non-parametric approach does not assume a particular form for the $z$-transform and takes advantage of the complex cepstrum properties. For the minimum-phase signals the complex cepstrum is causal, i.e. it equals zero at the negative quefrencies [24]. For such signals, the Hilbert transform provides a one-to-one relationship between the magnitude and phase spectra as follows

$$\arg[X_{MinPh}(\omega)] = -\frac{1}{2\pi} \arg[X_{MinPh}(\omega)] \ast \cot(\frac{\omega}{2}) \quad (6)$$

By replacing the $\arg[X_{MinPh}(\omega)]$ with $\arg[X(\omega)]$ based on Eq. (4), $\arg[X_{MinPh}(\omega)]$ can be computed. Alternatively, the minimum-phase component can be calculated by putting a proper filter on the cepstrum sequence. It should be noted that both of these approaches are very closely related, one operates in the frequency domain and one acts in the quefrency domain. If the independent variable was continuous both would return identical results, however, due to having discrete independent variables, the outcome of these two approaches would not be exactly the same. Fig 2(h) shows this slight difference which is due to the behaviour of the $\cot(\cdot)$ function as it tends to infinity at the edges. By increasing the FFT length such error reduces. We will use the cepstrum-based method henceforth because of its better numerical accuracy.

3.3. Source-Filter Modelling

Now, $\arg[X_{MinPh}(\omega)]$ should be decomposed into excitation and vocal tract components. To this end, some prior knowledge is required. However, apart from the source/filter issue, by looking at the $\arg[X_{MinPh}(\omega)]$ (Fig 2(h)), it can be imagined as a modulated signal with two major ingredients, namely carrier and message. The former varies fast and the later changes more slowly with respect to the independent variable, i.e. frequency. Based on this argument $\arg[X_{MinPh}(\omega)]$ may be expressed as follows

$$\arg[X_{MinPh}(\omega)] = Trend + Fluctuation \quad (7)$$

where the Trend element is the slowly-varying aspect and the Fluctuation relates to the rapidly changing component [35].
The advantages of the proposed method compared with the magnitude-based approach are twofold: higher frequency res-
In order to investigate the effectiveness of the proposed method, we used it as the basis of a feature extractor for speech recognition and compared its performance with other well-known features. Four simple approaches were taken for turning the filter component into a feature for ASR.

- **i)** $\arg[X_{VT}] \rightarrow DCT \Rightarrow PHVT$
- **ii)** $\hat{\tau}_{VT} \rightarrow DCT \Rightarrow GDVT$
- **iii)** $\hat{\tau}_{VT} \rightarrow MelFilterbank \rightarrow DCT \Rightarrow MFGDVT$
- **iv)** $\hat{\tau}_{VT} \rightarrow MelFilterbank \rightarrow Boost \rightarrow DCT \Rightarrow BMFGDVT$

where the rightmost name is the name assigned to each feature derived from the filter component of the phase spectrum.

For all features, we have used the default parameters reported in their respective publications. Frame length, frame shift and number of filters were set to 25 ms and 10 ms and 23, respectively. Feature vectors have been augmented by log-energy as well as delta and delta-delta coefficients. Cepstral mean normalization (CMN) is performed. In the proposed method, $\alpha$ coefficient (Eq. (10)) was set to 0.7 and brickwall lowpass filter with 20 taps was used for extracting the Trend.

Hamming window were applied for all features except for the proposed methods where Chebyshev (30 dB) window has been employed due to [15]. Aurora-2 [37] has been used as the database and the HMMs were trained from the clean data using HTK [38] based on the Aurora-2 standard recipe. Recognition results (average 0-20 dB) of the different magnitude-based and phase-based features are reported in Table 1.

### 4.2. Discussion

As seen, the proposed method outperforms the other magnitude and phase-based features despite its relative simplicity. In particular, the fact that it provides better performance than power normalized cepstral coefficients (PNCC) [39], is remarkable given the complexity of the PNCC. The relative robustness of the proposed method can be explained in part by the greater distinction of the formants arising from there being higher frequency resolution and less leakage which, in turn, decreases the confusion occurring after SNR reduction in the spectrum. Another important factor should be noted: As mentioned, the vocal tract component corresponds with the trend of the MelPh parts phase spectrum. Each point of the Trend may be considered as a pseudo-mean of the neighbouring points in the vicinity. This, in turn, increases the inertia of each of the Trend’s individual points. As a result, the tendency for a point to preserve its initial condition and resist disturbance is higher. This reduces the sensitivity to the noise and increases the feature’s robustness.

### 5. Conclusions

In this paper we proposed a novel phase-based method for the source-filter decomposition of speech. The minimum-phase part of the signal was computed through a Hilbert transform. Vocal tract and excitation components were then successfully deconvolved by Trend/Fluctuation analysis of the corresponding phase spectrum. This analysis clarifies the behaviour of the phase spectrum and the way in which it encodes information. The efficiency of the method in comparison with performing the same process in the log-magnitude (cepstrum) and GDF domains was discussed and illustrated. In addition, the vocal tract component was transformed into a feature vector and its effectiveness was evaluated in speech recognition. Recognition results demonstrate the efficacy of the proposed method. Notably, despite its simplicity, it outperforms recent robust feature extraction techniques such as PNCC. Given the centrality of the source-filter modelling, the proposed method paves the way for putting the phase spectrum to practical use by providing a foundation for speech signal processing through phase manipulation. Further optimization and studying the statistical behaviour of the proposed phase-based representations is a broad avenue for future research.
6. References


