

# Glottal Closure and Opening Instant Detection from Speech Signals

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## Abstract

This paper proposes a new procedure to detect Glottal Closure and Opening Instants (GCIs and GOIs) directly from speech waveforms. The procedure is divided into two successive steps. First a mean-based signal is computed, and intervals where speech events are expected to occur are extracted from it. Secondly, at each interval a precise position of the speech event is assigned by locating a discontinuity in the Linear Prediction residual. The proposed method is compared to the DYPSA algorithm on the CMU ARCTIC database. A significant improvement as well as a better noise robustness are reported. Besides, results of GOI identification accuracy are promising for the glottal source characterization.

## 1. Introduction

In speech processing, Glottal Closure Instants (GCIs) are referred to the instances of significant excitation of the vocal tract. These particular time events correspond to the moments of high energy in the glottal signal during voiced speech. Knowing the GCI location is of particular importance in speech processing.

For speech analysis, closed-phase LP autoregressive analysis techniques have been developed for better estimating the prediction coefficients, which results in a better estimation of the vocal tract resonances [1]. These techniques explicitly require the determination of GCIs. A wide range of applications also implicitly assume that these instants are located. In concatenative speech synthesis, it is well known that some knowledge of a reference instant is necessary to eliminate concatenation discontinuities. This motivated the use of GCIs in the famous TD-PSOLA algorithm [2] or as a means to remove phase mismatches [3]. GCI has also been used for voice transformation [4], voice quality enhancement [5], speaker identification [6], glottal source estimation [7], or speech coding and transmission [8].

Many methods have been proposed to locate the GCIs directly from speech waveforms. The earliest attempts relied on the determinant of the autocovariance matrix [9]. A study of the use of the Linear Prediction (LP) residual was investigated in [10]. Indeed, as GCIs correspond to instants of significant excitation, it is assumed that a large value in the LP residual is informative about the GCI location. In [11], GCIs were determined as the maxima of the Frobenius norm. An approach based on a weighted nonlinear prediction was proposed in [12]. In [13], an algorithm based on a wavelet decomposition was considered. Some techniques also exploit the phase properties due to the impulse-like nature at the GCI by computing a group delay function [14]. The DYPSA algorithm, presented in [15], estimates GCI candidates using the projected phase-slope and employs dynamic programming to retain the most likely ones. In [16], GCIs are located by the center-of-gravity based signal and then refined by using minimum-phase group delay functions derived from the amplitude spectra. More recently, au-

thors in [17] proposed to detect discontinuities in frequency by confining the analysis around a single frequency. In this latter work, GCIs correspond to the positive zero-crossings of a filtered signal obtained by successive integrations of the speech waveform and followed by a mean removal operation. Comparative studies of the most popular approaches were led in [15] and [17]. It was shown that the DYPSA algorithm and the technique proposed in [17] clearly outperformed other state-of-the-art methods.

On the other hand, very few works addressed the determination of Glottal Opening Instants (GOIs) from speech signals. Indeed, as the energy of excitation at GOIs is known to be weaker and more dispersed (resulting in more regular behaviour) than at GCIs [15], their automatic location remains a challenging problem. A method based on a multiscale product of wavelet transforms was proposed in [18], but no quantitative results were given.

This paper proposes a simple procedure to detect GCIs and GOIs from speech waveforms. The procedure is divided into two steps. First, an initial estimate of the GCI location is computed from a mean-based signal. This latter is obtained by calculating the mean of sliding windowed speech segments. This first estimation gives short intervals where GCIs are expected to occur. The second step aims at refining the GCI location by finding, for each interval, the largest LP residual value, which is assumed to correspond to the strongest impulse in the excitation signal.

The paper is structured as follows. Our proposed method is fully described in Section 2. In Section 3, we present our results obtained on the CMU ARCTIC database [19]. As the performance of our technique depends on the window length used for computing the mean-based signal, the impact of this parameter is first discussed. We then compare our method with the DYPSA algorithm [15] according to their GCI detection performance. The accuracy we obtained on GOI determination is also presented. Besides the noise robustness of both techniques is analyzed. Finally we conclude in Section 4.

## 2. Proposed method

The proposed method consists of two successive steps. During the first step (Section 2.1), a mean-based signal is computed, allowing the determination of short intervals where GCIs and GOIs are expected to occur. As for the second step (Section 2.2), it consists of a refinement of the accurate locations from the LP residual signal.

### 2.1. Interval determination from a mean-based signal

In [17], authors argue that a discontinuity in the excitation is reflected over the whole spectral band, including the zero frequency. For this, they use the output of 0-Hz resonators to locate GCIs. Inspired from this observation, we focus our analysis on a mean-based signal. If  $s(n)$  denotes the speech waveform, the

mean-based signal  $y(n)$  is computed as:

$$y(n) = \frac{1}{2N+1} \sum_{m=-N}^N w(m)s(n+m) \quad (1)$$

where  $w(m)$  is a windowing function of length  $2N+1$ . In our experiments we used a Blackman window whose length is chosen as explained in Section 3.1.

Figures 1(a) and 1(b) show an example of a voiced speech segment together with its corresponding mean-based signal. This latter presents the important property to evolve at the local pitch rhythm. However this signal in itself is not sufficient for accurately locating the GCIs. Indeed, we reported through our observations that a GCI occurs at a non-constant position between the minimum and the following positive zero-crossing of the mean-based signal. For this, we define intervals where the precise location of the GCI is expected to lie. In the same way, we observed that the GOI position falls within an interval defined by the maximum and the following negative zero-crossing of the mean-based signal. To ensure that the previous interval contains the real GOI, a margin of 0.25 ms is added at both sides of it. In addition, to avoid a possible irrelevant drift in the mean-based signal, previous zero-crossings are replaced by the midpoints between two successive extrema. Figures 1(c) and 1(d) exhibit such intervals extracted from the mean-based signal of Fig. 1(b) respectively for GCIs and GOIs.

## 2.2. GCI and GOI location refinement from the LP residual

Intervals obtained in the previous Section give "fuzzy" short regions where particular events (GCI or GOI) should happen. The goal of the current step is to associate an accurate location of an event within an interval. For this, we rely on the Linear Prediction (LP) residual. Indeed, after removing an approximation of the vocal tract response, one can expect that significant impulses in the excitation signal will be reflected in the LP residual. We can consequently assume that the event location corresponds to the strongest peak of the LP residual within the interval. Figures 1(e) and 1(f) show the time-aligned differenced electroglottograph (EGG) and the LP residual. Combining the intervals extracted from the mean-based signal with a peak picking method on the LP residual allows to accurately and unambiguously detect both GCIs and GOIs. Nevertheless while the impulse at the GCI significantly emerges from its neighborhood, the behaviour at the GOI is more regular since the excitation presents a discontinuity more spread out and with a weaker strength. As a consequence, obtaining for GOIs an identification accuracy comparable to what can be achieved for GCIs remains a challenging problem (cf Section 3.2).

## 3. Results

The experiments presented in this Section were achieved on the CMU ARCTIC database (publicly available in [19]) containing 3 speakers: BDL (US male), JMK (Canadian male) and SLT (US female). The database consists of 1132 phonetically balanced utterances for each speaker (about 50 min), giving a total duration of around 2h40min. We compare our proposed method with the DYPSA algorithm [15] whose implementation can be found in [20]. Both techniques are applied on 16 kHz speech waveforms and EGG signals are used as a reference. Note that EGGs were time-aligned to compensate the delay between the laryngograph and the microphone. A 24-th order LP analysis was performed on 25ms long Hanning-windowed frames,

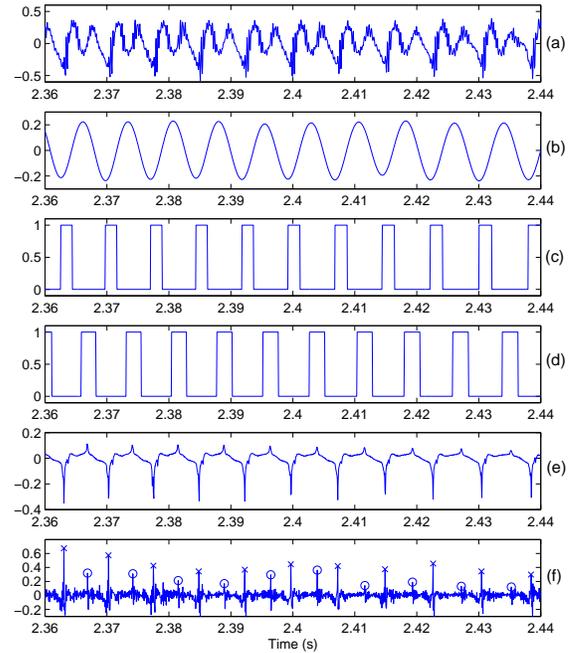


Figure 1: Example of GCI and GOI extraction on a voiced segment: (a) the speech signal, (b) its corresponding mean-based signal, (c) interval of GCI presence derived from the mean-based signal (between the minimum and the following positive zero-crossing), (d) interval of GOI presence derived from the mean-based signal (between the maximum and the following negative zero-crossing, with a margin of 0.25 ms), (e) aligned differenced electroglottograph, (f) the LP residual with the detected GCIs (x) and GOIs (o).

shifted every 5 ms, and the LP residual was obtained by inverse filtering. To assess the performance of the methods we employed the measures defined in [15], namely:

- the Identification Rate (IDR),
- the Miss Rate (MR),
- and the False Alarm Rate (FAR),

and two indicators characterizing the timing error probability density:

- the Identification Accuracy (IDA), i.e the standard deviation of the distribution,
- the accuracy to  $\pm 0.25$  ms, i.e the rate of detections for which the timing error is smaller than this bound.

### 3.1. Impact of the window length

As explained in Section 2.1, our method is controlled by only one parameter (once the LP analysis is fixed): the window length used in Equation 1. The influence of this parameter on the misidentification rate ( $= 1 - IDR$ ) is illustrated in Figure 2 for the female speaker SLT. Optimality is seen as a trade-off between two opposite effects. A too short window causes the appearance of spurious extrema in the mean-based signal, giving birth to false alarms. On the other hand, a too large window

smooths it, affecting in this way the miss rate. However we clearly observed for the three speakers a valley between 1.5 and 2 times the average pitch period  $T_{0,mean}$ . Throughout the rest of this article we used a window whose length is  $1.75 \cdot T_{0,mean}$ . A pitch-dependent approach could also be envisaged but with the drawback of requiring a reliable pitch estimator.

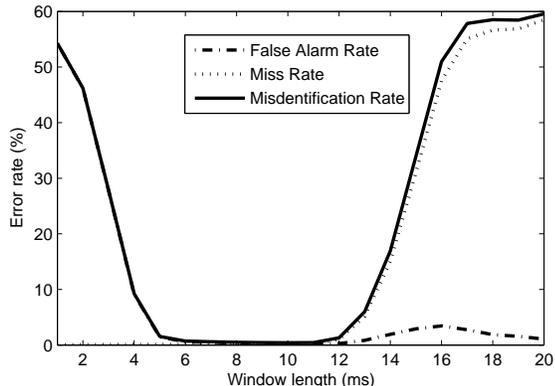


Figure 2: Effect of the window length on the misidentification rate for the speaker SLT, whose average pitch period is 5.7 ms.

### 3.2. Identification performance

Table 1 details the identification efficiency for both DYPESA and proposed methods. A clear advantage can be noticed in favor of our technique over all rates and speakers. Since this performance is conditioned in our method by the mean-based signal, results are sensibly the same for GCI and GOI detection. On the opposite, error probability densities depend on the LP-based location refinement step and the accuracy consequently differs for GCIs and GOIs. Table 2 summarizes comparative accuracy results for the DYPESA algorithm and for our method employed for GCI as well as GOI detection. It can be noted that our proposed technique outperforms DYPESA except for speaker JMK whose results are almost similar. It also turns out that GOIs are less precisely located than GCIs, which was expected for the reasons underlined in Section 2.2. Nonetheless, despite these inherent difficulties, the proposed technique appears to give a rather efficient estimation of the GOI position. Leading to the same conclusions, figures 3, 4 and 5 depict the histograms averaged over all the speakers of the timing error made by the DYPESA algorithm on the GCI determination, and by the proposed method on both GCIs and GOIs respectively. Among others, it can be seen that our technique is more accurate than DYPESA and that 84% of identified GOIs are located with an absolute error lower than 1 ms.

Speaker	Method	IDR (%)	MR (%)	FAR (%)
BDL	Dypsa	96.81	1.78	1.41
BDL	Proposed	98.89	0.61	0.50
JMK	Dypsa	98.17	1.50	0.33
JMK	Proposed	98.59	1.30	0.11
SLT	Dypsa	97.44	1.43	1.13
SLT	Proposed	99.34	0.17	0.49

Table 1: Comparative results in terms of Identification Rate (IDR), Miss Rate (MR) and False Alarm Rate (FAR).

Speaker	Method	Event	IDA (ms)	Accuracy to $\pm 0.25$ ms (%)
BDL	Dypsa	GCI	0.34	81.7
BDL	Proposed	GCI	0.25	88.8
BDL	Proposed	GOI	0.49	65.2
JMK	Dypsa	GCI	0.41	74.2
JMK	Proposed	GCI	0.41	74.0
JMK	Proposed	GOI	0.69	48.3
SLT	Dypsa	GCI	0.38	75.1
SLT	Proposed	GCI	0.27	83.5
SLT	Proposed	GOI	0.63	41.2

Table 2: Comparative results in terms of Identification Accuracy (IDA) and accuracy to  $\pm 0.25$  ms, characterizing the error probability densities.

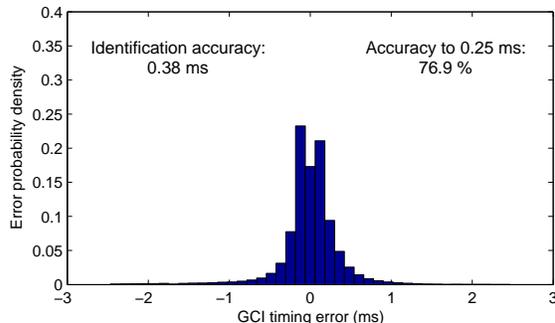


Figure 3: Histogram of the GCI timing error averaged over all speakers for the DYPESA algorithm.

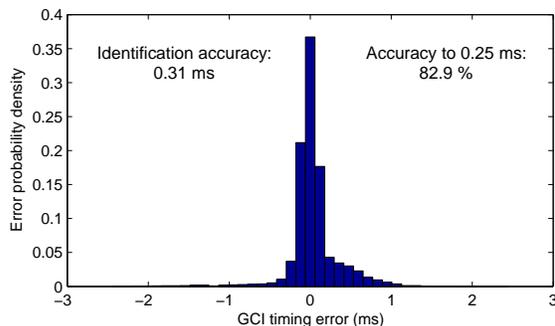


Figure 4: Histogram of the GCI timing error averaged over all speakers for the proposed method.

### 3.3. Noise robustness

Methods are here compared according to their noise robustness. For this, a white Gaussian noise and a babble noise (from a cafeteria environment) were added at different levels to the speech signals. The Signal-to-Noise Ratio (SNR) varies from -10 dB (extremely adverse conditions) to 80 dB (almost clean speech). Figure 6 reports the evolution of the misidentification rate with the noise level. Our technique remains almost insensitive up to 0 dB while DYPESA begins to degrade from 30 dB before being severely affected from 10 dB. This observation holds for both noise type.

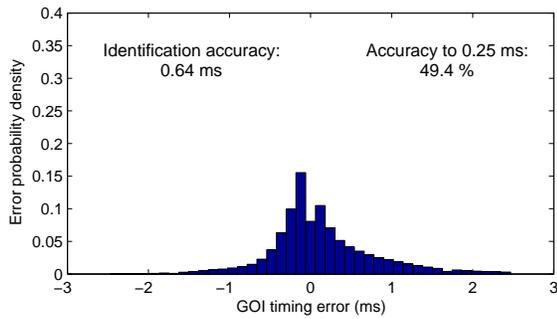


Figure 5: Histogram of the GOI timing error averaged over all speakers for the proposed method.

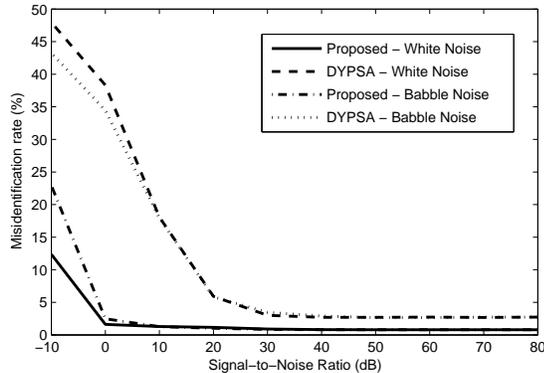


Figure 6: Comparison of the performance degradation with additive white and babble noises for the DYPSA and proposed methods.

## 4. Conclusion

This paper proposed a new procedure for detecting the GCIs and GOIs directly from speech signals. The procedure was divided into two successive steps. The first one computed a mean-based signal and extracted from it intervals where speech events were expected to occur. This step guaranteed good performance in terms of identification rate. The second one refined the location of the speech events within the intervals by inspecting the LP residual. As for it, this step ensured good performance in terms of identification accuracy. Our proposed method was compared to the DYPSA algorithm on the CMU ARCTIC database. Through our experiments, we reported a significant improvement in GCI detection efficiency as well as in noise robustness. In addition our method also allowed to determine the GOIs locations with an encouraging precision, although not yet comparable to what can be achieved for GCIs. As future work we plan to enhance the GOI locations by analyzing the open quotient trajectories. We also plan to investigate the characterization of the glottal source by combining the proposed method with other source-filter deconvolution approaches.

## 5. Acknowledgments

Thomas Drugman is supported by the “Fonds National de la Recherche Scientifique” (FNRS).

## 6. References

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