A comparative study of glottal open quotient estimation techniques

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Abstract

The robust and efficient extraction of features related to the glottal excitation source has become increasingly important for speech technology. The glottal open quotient (OQ) is one relevant measurement which is known to significantly vary with changes in voice quality on a breathy to tense continuum. The extraction of OQ, however, is hampered in the time-domain by the difficulty in consistently locating the point of glottal opening as well the computational load of its measurement. Determining OQ correlates in the frequency domain is an attractive alternative, however the lower frequencies of glottal source spectrum are also affected by other aspects of the glottal pulse shape thereby precluding closed-form solutions and straightforward mappings. The present study provides a comparison of three OQ estimation methods and shows a new method based on spectral features and artificial neural networks to outperform existing methods in terms of discrimination of voice quality, lower error values on a large volume of speech data and dramatically reduced computation time.

Index Terms: Open Quotient, Glottal source, Voice quality, Artificial Neural Networks

1. Introduction

Speech technology applications are increasingly exploiting features relating to the glottal excitation source. This has led to novel and promising developments in several areas. For instance, recent developments in speech synthesis [1, 2] and voice modification [3] involve parametric modelling of the glottal source which can allow effective modification of voice quality. Other approaches to developing speech synthesis systems, which can allow variation in voicing style, have involved the use of a range of voice quality features for the partitioning and clustering of corpora of expressive speech [4]. Voice quality features related to breathiness and tenseness have found further use in other speech processing applications, e.g., speech recognition [5], speaker identification [6] and emotion classification [7, 8].

One particularly salient measurement of the glottal pulse, thought to be useful for discriminating breathy to tense voice [9, 10], is the glottal open quotient (OQ, [11]). OQ can be defined as the duration of the glottal open phase normalised to the local glottal period. Besides being useful for disambiguating voice qualities, OQ can also be used in combination with detected glottal closure instants (GCIs, [12]) to locate the glottal opening instant (GOI). This in turn can be used to optimise closed-phase glottal inverse filtering.

Despite the potential usefulness of this parameter, its measurement suffers from a lack of robustness due to the difficulty in consistently locating the point of glottal opening [13]. One common approach is to fit a model to the estimated glottal source signal in order to determine OQ. However, the standard error criterion minimised in the model fitting does not ensure consistency in marking the point of glottal opening. This perhaps explains why OQ derived from a Liljencrants-Fant (LF, [14]) glottal model fit in [15] was less effective at discriminating voice quality than parameters derived from direct measures. A further drawback of this approach is that it usually has a high computational load. Others have attempted to find robust correlates of OQ. The quasi-open quotient (QOQ, [16]) is a frequently used correlate of OQ which involves derivation of the quasi-open phase based on amplitude measures of the glottal pulse. These time domain approaches, however, can be seriously impaired if there is negative signal polarity or phase distortion in the signal which can often occur in less than ideal recording conditions.

Another approach is to derive a correlate of OQ from frequency domain measurements. An often used parameter is the difference in amplitude between the first two harmonics (H1-H2) measured in the narrowband spectrum of the inverse filtered, or formant corrected, speech signal [17]. Although this has been utilised as a reasonably effective correlate of OQ, the lower frequencies of the glottal source spectrum are known to also be significantly affected by the skewness of the glottal pulse [18]. This has a confounding effect on the H1-H2 measurement, in terms of it being an OQ correlate. This issue has meant that there is as of yet no effective closed-form solution for measuring OQ in the frequency domain, nor a method for straightforward mapping between frequency and time domain.

To address this, the current study looks to assess two existing methods for estimating OQ as well as a new method involving the use of spectral features as input to artificial neural networks (ANNs) in order learn the mapping from spectral measurements to the time domain OQ values. The three methods are assessed in terms of error rates on a large database of speech, the ability to discriminate voice quality and in terms of computational load.

2. OQ estimation techniques

2.1. LF model fitting - Strik-LF

The Strik-LF model fitting method operates on the glottal source signal estimated, in this case, by Iterative Adaptive Inverse Filtering (IAIF, [26]). The first step involves finding an initial set of LF model parameters which are then refined during an optimisation procedure. In order to avoid the negative effect of high-frequency components on the fitting, a low-pass filtering operation is first applied. This is done by convolving the

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voice source signal with an 11-point Blackman window, which has the characteristic of having a ripple-free impulse response [22]. The model fitting starts from a given glottal closure instant (GCI), as detected using the SEDREAMS algorithm, (see [27]). The time point of the main excitation, t_e, is obtained by searching nearby the GCI location for the maximum negative amplitude. This amplitude is chosen as the EE value of the model. Then a search is done for the first zero-crossing prior to t_e. This point is assigned as t_p. The point of glottal opening, t_o, is obtained by continuing the 'leftward' search until the pulse amplitude descends to below a certain threshold. We set this threshold as 0.1 times the maximum positive amplitude of the present estimated voice source pulse. To obtain an initial t_a value, [28] suggest using an FFT based approach. However, our experience of using this approach is that it frequently gives unsuitable t_a values. Instead we fix the initial Ra value of 0.02, and t_a is calculated from this. A similar approach is used in the SKY voice source analysis software [29]. OQ can be derived from a fitted LF model by normalising the duration from t_o to t_e, to the local glottal period.

2.2. YAGA

The Yet Another GCI/GOI Algorithm (YAGA [30]) uses a variety of methods including: wavelet analysis, the group delay function and N-best dynamic programming. GCI candidates are detected in YAGA by first estimating the glottal source with IAIF. The multi-scale product of the stationary wavelet transform (SWT) is used to highlight discontinuities in the glottal source, by using information across the wavelet scales. These discontinuities are detected using the group-delay function, and GCI candidates are measured as negative-going zero-crossings. False alarms are then removed using a similar N-best dynamic programming approach as in DYPSA [12]. YAGA uses similar cost elements to those used in DYPSA, with modification of the inter-pulse similarity cost and a further cost for discriminating GCIs and GOIs. OQ is then derived with $\frac{\text{GCI(n)}-\text{GOI(n)}}{\text{GCI(n)}-\text{GCI(n-1)}}$, where n is the index of the n^{th} glottal pulse.

2.3. ANN-OQ

In the new method presented here (named ANN-OQ), rather than focus on a limited part of the spectrum (e.g., the first two harmonics), we obtain a rich spectral description and use this as input to ANNs. Furthermore, we avoid estimation of GCIs, f_0 and harmonics which may negatively impact on the robustness of the method, particularly for analysis of speech recorded in less than ideal conditions. For this we extract 12 Mel-frequency cepstral coefficients (MFCCs) measured on 32 ms Hanning windowed with a 10 ms shift. Note that the first MFCC related to signal energy is omitted. Δ and $\Delta\Delta$ coefficients are also included, resulting in a 36-dimensional feature vector. It is hypothesised that this richer spectral description may help disambiguate OQ from the confounding effect of the skewness of the glottal pulse.

We apply an artificial neural network (ANN) approach in order to approximate the OQ values from the MFCC features. In general we utilise an ANN to learn a mapping f from the input feature space I (typically $\mathbb{R}^n$, i.e. the extracted MFCC features) to the target space T (in this case $\mathbb{R}$, i.e. the estimated OQ value): $f(\mathbf{x}) : \mathbf{x} \in I \rightarrow \mathbf{y} \in T$, where $\mathbf{x}$ denotes the input vector and $\mathbf{y}$ the output of the approximator f.

We chose the well known multi-layer perceptron (MLP) as the network type of choice, as it fulfills the universal approximator theorem [19] and is computationally inexpensive once the network parameters are trained. The theorem states that the MLP is capable of approximating any continuous function on a compact interval of $\mathbb{R}^n$ (which is provided as OQ $\in [0, 1]$) with a small error.

Specifically, the network was set-up as a two layer MLP with one hidden layer containing 100 neurons, all fully connected to the input and the output layer. The hidden layer neurons use $\tanh$ as a transfer-function and the output neuron a linear transfer-function, as this is optimal for function approximation. The training was conducted using a standard error back-propagation algorithm [20].

3. Experimental setup

3.1. Speech data

Three speech databases were used as part of the present study. The selection of speech data was restricted to databases where there were simultaneous electro-glottographic (EGG) recordings, as this was required for deriving objective reference values.

The first was a set of Finnish vowels, including recordings of 6 female and 5 male speakers (used in a previous study: [15]). The speakers were originally asked to produce eight Finnish vowels /ɑ e i o u y æ ø/ using breathy, neutral and pressed phonation types. Participants were trained with producing the voice qualities before recording. While conducting the recording, speakers were asked to repeat the utterance with stronger emphasis on the voice quality when it was necessary. Audio was recorded using high quality recording equipment (a unidirectional Sennheiser electret microphone with a preamp, LD MPA10e Dual Channel Microphone Preamplifier). Each utterance was repeated three times resulting in 792 speech segments. However, for 4 of the speakers the EGG signals were deemed unsuitable for obtaining reliable reference values. This reduced the database to 7 speakers (3 male, 4 female), with 504 utterances in total. We call this the Voice Quality database.

Also included in the study were all speech data from the ARCTIC database [21] which had EGG signals available. This totalled 5 speakers: two American male (BDL; 1132 utterances, KED; 450 utterances), an American female (SLT; 1131 utterances), a Canadian male (JMK; 1114 utterances) and a UK male (RAB; 1946 utterances).

The last database used in the present study was the APLAWD dataset (see [12]). This contains speech data from 5 males and 5 females producing 10 repetitions of 5 phonetically balanced sentences. Note that this database was solely used for training the ANN-OQ method. Although the APLAWD database has less volume of data than ARCTIC, the fact that is balanced for gender, that the speakers display a fairly wide variety of inherent voice quality (and, hence, of OQ) and that it has reasonable phonetic coverage makes it a more suitable training set for the ANN-OQ method.

3.2. Reference values

Obtaining objective reference values for quantitatively evaluating glottal source analysis is extremely difficult, and indeed the absence of objective references has hampered developments in this field. Various evaluation methods have been used in previous studies each with their own shortcomings. Analysis can be carried out on synthetic speech signals with known reference parameter values (see e.g., [22, 23]). However these signals may lack the details that often cause trouble for voice source

parameterisation (e.g., the presence of aspiration noise). Another approach is to evaluate parameterisation on the basis of the ability of extracted parameters to differentiate voice quality (e.g., [15, 23, 24]), however this does not directly evaluate the parameterisation.

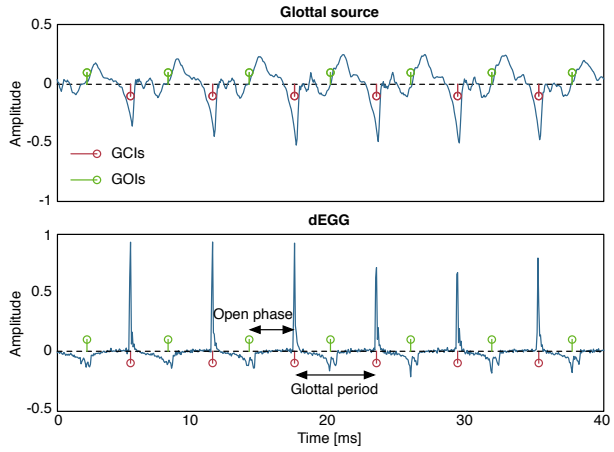

Figure 1: Differentiated glottal source signal (top) estimated by IAIF and the derivative EGG signal (bottom) both shown with GCIs (red) and GOIs (green) as estimated by SIGMA.

We derive OQ reference values from the simultaneous EGG signals available with the data. This approach also has its drawbacks, in particular the uncertainty when mapping from the physiological to the acoustic domain as well as the fact that the discontinuities relating to glottal opening can be often less clearly identified than those corresponding to the GCI. Nevertheless, this approach was deemed necessary in order to have objective target values from large amounts of data. Glottal closure instants (GCIs) and glottal opening instants (GOIs) were derived from the EGG signal using the SIGMA method [25], see Figure 1. This method involves applying a stationary wavelet transform and subsequent use of the group delay function with post-processing using Gaussian mixture modelling. OQ is then calculated in the same manner as for YAGA (see Section 2.2). Although there can occasionally be inaccuracies in the GOI estimation using SIGMA, this was deemed to be the most suitable approach for deriving reference OQ values. Note that the decision on the presence of voicing was also determined from EGG and this was used to avoid unvoiced OQ values in all analysis methods.

3.3. Experiments

Three experiments are carried in order to assess the performance of the OQ estimation techniques. The first experiment is carried out on the Voice Quality database where the data displays wide variation in OQ. The experiment examines the size of the error on OQ for the three methods as well as the ability to discriminate breathy, modal and tense voice. Note that for this experiment the ANN-OQ method is trained using a leave-one-speaker-out approach, where OQ estimates for given speaker are obtained using the method trained on all other speakers in the Voice Quality database, as well as the entire APLAWD database. For the second experiment, OQ values are derived using all the methods for the ARCTIC database. This experiment examines the performance of the three OQ estimation methods on a large phonetically balanced set of speech data. The ANN-OQ method for this testing is trained on all of the Voice Quality and APLAWD data. For the final experiment, the computation speed of the three methods is compared as for certain applications extremely fast glottal parameterisation may be required. For Strik-LF, we compute the runtime just for the algorithm itself and not the GCI detection and inverse filtering which are required prerequisites. We reduce the maximum number of iterations for the optimisation algorithms to 5. Although the analysis is carried out within the Matlab environment, we use compiled C-code for the LF model function which is known to have a high computational complexity.

4. Results

4.1. Experiment 1: Voice quality database

The results for the first experiment are illustrated in Figure 2, where the absolute error between the estimated OQ values and the reference values are plotted as a function of voice quality for the three approaches. Note that for ANN-OQ, values are derived on a speaker independent basis (i.e. OQ values for the held out speaker). It can be observed that the error values are comparatively low for the ANN-OQ method across the three voice qualities. For the YAGA method the error scores increase from breathy to modal and from modal to tense. We examined this and found that the YAGA method tends to consistently underestimate the duration of the glottal closed phase. As a result the error is observed to be highest for the voice quality with the longest glottal closed phase, i.e. tense voice.

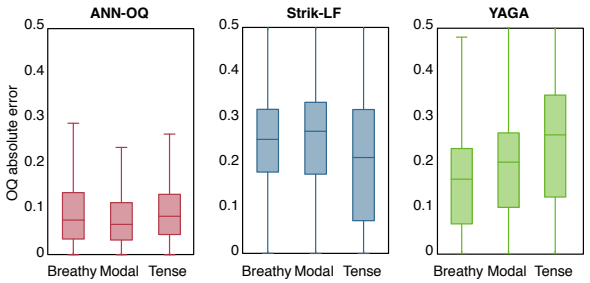

Figure 2: Absolute error on OQ values for the three approaches, plotted as a function of voice quality label.

These findings are supported by the evidence shown in Figure 3. Unsurprisingly, the OQ values derived from the EGG signal, using the SIGMA method, provide the best discrimination of the voice qualities. The ANN-OQ closely approximates this, though with less effective discrimination of breathy and modal voice. Although OQ values from the Strik-LF method do indeed vary with voice quality, they display wide distributions and considerably higher OQ values than the reference for breathy and modal voice. This is due to inconsistency of marking the point of glottal opening combined with, again, a frequent underestimation of the duration of the glottal closed phase, particularly for modal voice. The level of discrimination seen here corroborates previous analysis using the same data and parameterisation method [15]. The YAGA method is not observed to vary with changes in voice quality.

4.2. Experiment 2: Large phonetically balanced database

For the second experiment we investigate the performance of the three methods on a different corpus recorded under differ-

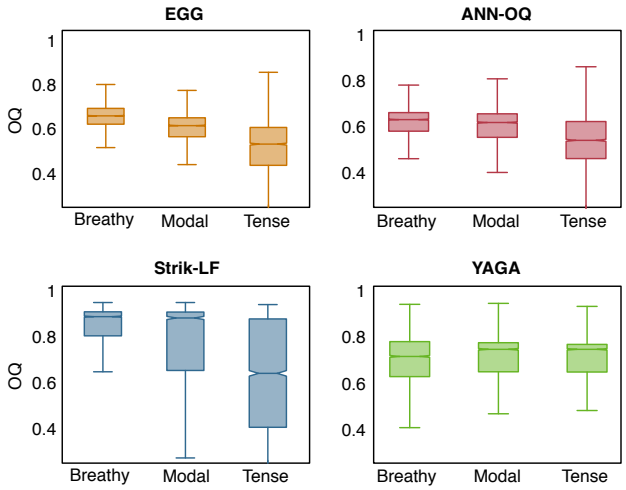

Figure 3: Observed OQ values for different voice qualities for the reference method (EGG), the novel approach (ANN-OQ), and the standard approaches Strik-LF and YAGA.

ent conditions, and containing several speakers and a wide phonetic coverage. Again we derive OQ values using the ANN-OQ, Strik-LF, and YAGA methods, and compare the absolute error to the reference OQ values for the ARCTIC dataset. The results for this test are summarised in Table 1 and Figure 4. We observe, that the new method ANN-OQ outperforms YAGA and Strik-LF for all the five speakers. The mean improvement of the distance to the reference OQ values over the YAGA method lies between -0.22 ($\sigma = 0.13$) for speaker RAB and -0.06 ($\sigma = 0.11$) for speaker SLT. The mean improvement of the distance to the reference values over the Strik-LF model lies between -0.19 ($\sigma = 0.16$) for speaker JMK and -0.02 ($\sigma = 0.16$) for speaker RAB. As there are a vast amount of OQ observations we only report the η^2 effect sizes for the conducted ANOVA tests in Table 1. According to [31], we approach the threshold for strong effects ($\eta^2 > 0.4$) for several speakers in the ARCTIC dataset (note, that all results were statistically significant). It is interesting to note that the ANN-OQ approach strongly outperforms one of the approaches for all speakers except for speaker BDL, where no strong improvement could be observed.

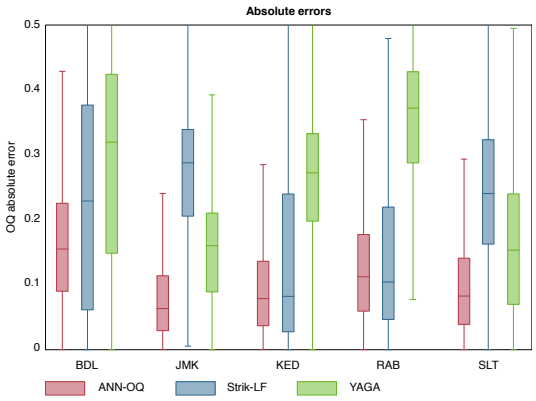

Figure 4: Distributions of absolute error on OQ for the three approaches and separated by speaker in the ARCTIC database.

Table 1: Mean absolute differences between errors for the three methods as computed against the reference OQ values. Negative μ values indicate that the ANN-OQ method outperforms the comparison method. The effect sizes η^2 are computed as the sum of squares within the compared groups divided by the sum of squares of the total set.

	ANN-OQ vs. YAGA		**ANN-OQ vs. Strik-LF**	
Speaker	$\mu(\sigma)$	η^2	$\mu(\sigma)$	η^2
BDL	-0.13 (0.18)	0.04	-0.07 (0.21)	0.01
JMK	-0.07 (0.11)	0.10	-0.19 (0.16)	0.38
KED	-0.16 (0.14)	0.38	-0.05 (0.17)	0.03
RAB	-0.22 (0.13)	0.31	-0.02 (0.16)	0.00
SLT	-0.06 (0.11)	0.06	-0.15 (0.15)	0.23

4.3. Experiment 3: Computational load

For the final experiment, we compare the runtime performance of the three OQ estimation methods. We compute the OQ values for all three approaches on the speakers BDL (male) and SLT (female) on an Intel Core i7 (3.30 GHz) machine with 12 cores and 16 GB memory running a 64bit version of Windows 7 and Matlab R2011b. We compare the relative runtime in % of realtime. As expected, ANN-OQ clearly outperforms YAGA and Strik-LF with an average of 0.41 % for BDL and 0.42 % for SLT. The runtime of YAGA is about 30 times higher with 15.17 % for BDL and 15.30 % for SLT. Strik-LF is computationally, the most intensive approach with a runtime of about 2 times realtime, i.e. 178.64 % for BDL and 226.45 % for SLT. It is seen that the performance of ANN-OQ and YAGA remain constant over different speakers, whereas the performance of Strik-LF is dependent on the speaker's f_0 (mean f_0: around 115 Hz for BDL; around 170 Hz for SLT).

5. Discussion and conclusion

In the present study, we assess the performance of three methods for estimating glottal open quotient (OQ), including a new method based on MFCCs and artificial neural networks (ANNs). Results show that for the new method (ANN-OQ), OQ estimates are closest to the reference OQ calculated from the electro-glottographic (EGG) signal on a vowel database with wide voice quality variation as well as on a large database of phonetically balanced speech. Additionally, the ANN-OQ approach is computationally inexpensive and clearly outperforms the standard approaches in terms of computational load. One further benefit is that the ANN-OQ method does not rely on GCI, f_0 or harmonic measurement, or glottal inverse filtering. This may contribute significantly to its robustness. For future work we intend to assess effect on performance of different spectral representations as well as the robustness of the new method to degraded conditions (e.g., additive noise). We also intend to exploit this measurement for discriminating voice quality in corpora of expressive speech.

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