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Research Article

Jitter Estimation Algorithms for Detection of Pathological Voices

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This work is focused on the evaluation of different methods to estimate the amount of jitter present in speech signals. The jitter value is a measure of the irregularity of a quasiperiodic signal and is a good indicator of the presence of pathologies in the larynx such as vocal fold nodules or a vocal fold polyp. Given the irregular nature of the speech signal, each jitter estimation algorithm relies on its own model making a direct comparison of the results very difficult. For this reason, the evaluation of the different jitter estimation methods was target on their ability to detect pathological voices. Two databases were used for this evaluation: a subset of the MEEI database and a smaller database acquired in the scope of this work. The results showed that there were significant differences in the performance of the algorithms being evaluated. Surprisingly, in the largest database the best results were not achieved with the commonly used relative jitter, measured as a percentage of the glottal cycle, but with absolute jitter values measured in microseconds. Also, the new proposed measure for jitter, LocJitt, performed in general is equal to or better than the commonly used tools of MDVP and Praat.

1. Introduction

Most voice-related pathologies are due to irregular masses located on the vocal folds interfering in their normal and regular vibration. This phenomenon causes a decrease in voice quality, that is, usually the first symptom of this type of disorders. In the past, the only way to measure voice quality was by applying perceptual measurements denoting the existence or absence of several voice characteristics [1]. There has been an increasing need for techniques that can evaluate voice quality in an objective way, providing a robust and reliable measurement of important acoustic parameters in voice [2]. With the recent development in technology, quality equipment and sophisticated software are now available to analyse the speech signal in order to estimate numerous parameters that indicate amplitude and frequency perturbations, the level of air leakage, the degree of turbulence, and so forth. The implementation of real-time analysis tools can give an important and instantaneous feedback of voice performance for both voice therapy and voice coaching procedures.

One of the most commonly used tools for this purpose is the Multidimensional Voice Program (MDVP) produced by KayPENTAX [3]. This commercial software tool is able to perform different types of acoustic analysis on the speech signal producing a large number of parameters. The MDVP is usually sold together with the KayPENTAX's Computerized Speech Lab, a hardware platform for digital voice recording, making its use very common among health professionals.

Another commonly used speech analysis tool is Praat [4], created by Paul Boersma and David Weenink of the Institute of Phonetic Sciences, University of Amsterdam. This free software is used by speech researchers, and it has a wider range of use than MDVP although with a steeper learning curve.

In this work we will focus on the estimation of irregularities in the vibration of the vocal folds that is commonly measured by the jitter parameter. Jitter measures the irregularities in a quasi-periodic signal and can account for variations in one or more of its features, like period, amplitude, shape, and so forth [5]. In the case of speech signal, its definition is less clear since the signal is very irregular. Even a sustained vowel produced by a professional speaker can hardly be considered a periodic signal. This way, the jitter of a voiced speech signal is usually taken as a measure of the change in the duration of consecutive glottal cycles. When this definition is applied to a sustained vowel with a constant average glottal period, the presence of jitter indicates that there are some periods that are shorter while others are longer than the average pitch period.

Both MDVP and Praat have the possibility of producing an estimate of the amount of jitter in a sustained vowel. However, it is known that MDVP system has a tendency to score jitter values above the ones calculated by Praat; when applied to the same speech signal they provide different estimates [6]. Apart from these there are other methods to estimate jitter, and the question is on how to compare them.

In this paper we present the results of our evaluation of 3 jitter estimation methods including the one used by MDVP and Praat. The goal of this study is not to develop a system for the detection of pathologic voices [7–9] but solely to understand the relative performance of the 3 jitter estimation techniques in this task.

The paper starts by presenting the glottal source and vocal tract models used in this work, followed by a description of the speech material that was used in the evaluation process. Next we present some methods for marking fixed points in the glottal cycle as required by the jitter estimation algorithms. We formalise the three jitter models that were used, followed by a description of the jitter estimation algorithms that were evaluated. A comparison of the algorithms for both pitch marking and jitter estimation is then presented. A set of 14 tools, combining the different algorithms, are then evaluated in their ability to detect pathological voices. Finally we present the conclusions and some ideas for future work.

2. Voice Source Model

Voice production starts with the vibration of the vocal folds, which can be more or less stretched to achieve higher or lower pitch tones. In normal conditions and in spite of this pitch variation ability, phonation is considered stabilized and regular. Any transformation on the vocal fold's tissue can cause an irregular, nonperiodic vibration which will change the shape of the glottal source signal from one period to the next, introducing jitter [10]. The same problem can occur in amplitude. If, for instance, the vocal folds are too stiff, they will need a higher subglottal pressure to vibrate. The glottal cycle can thus be irregularly disturbed also in amplitude, originating shimmer. Not less important is the possible existence of high frequency noise, especially during the closed phase of the glottal cycle, originated by a partial closure of the vocal folds, which will cause an air leakage through the glottis, providing a turbulence effect. All these phenomena affect the glottal source signal, but we do not have direct access to this signal, only to the sound pressure radiated at the lips. The estimation of the glottal source signal from the voice signal is not a simple task. Research in this field shows that it is reasonable to approximate the influence of the vocal tract by a linear filter. Using this approximation, the voice signal can be filtered by inverse of this filter to obtain an estimate of the glottal source signal [11]. In this work we will use a noninteractive approach that does not consider the influence of the supraglottis vocal tract nor the influence of the subglottis cavities on the glottal flow. As a consequence, we assume that the source and filter parameters are independent.

3. Vocal Tract Model

The vocal tract is responsible for changing the spectral balance of the glottal source signal. By changing the vocal tract shape the speaker can modify its resonance frequencies to produce a wide variety of different sounds. Humans use the evolution in time of the resonance frequencies to produce speech. In this work, we model the vocal tract by an all-pole filter estimated using a Linear Prediction Analysis (LPC) [12]. LPC is a powerful and widely used tool for speech analysis that assumes the already mentioned separation of the source signal from the vocal tract filter. The contribution of the vocal tract resonances estimated by the LPC algorithm can be removed from the speech signal by inverse filtering. This process produces an estimate of the glottal source signal, also called residue. The ability to change the residue for other similar inputs, with different fundamental frequencies or amplitudes, and applying them to the original vocal tract filter, allows the production of many combinations of synthetic voices.

4. Speech Data

The evaluation of the jitter detection algorithms was also conducted on real voices. For this purpose, two databases were used: the Disordered Voice Database (MEEI) provided by KayPENTAX, and a database named DB02 specifically created for this study.

The Disordered Voice Database (MEEI) was developed by the Massachusetts Eye and Ear Infirmary (MEEI) Voice and Speech Lab. It includes more than 1400 voice samples from approximately 700 subjects [13]. The database includes samples from patients with a wide variety of organic, neurological, traumatic, psychogenic, and other voice disorders, together with normal subjects. For this work, a group of 50 pathological voices and 50 normal voices was randomly chosen from this data set.

The DB02 database was acquired in similar conditions as the MEEI database using the Computerized Speech Lab 4150 acquisition system from KayPENTAX, together with a dynamic low impedance microphone (SURE SM48). The CSL 4150 provides a 16-bit A/D conversion, preamplification, and antialiasing filtering. All voices for this study were recorded with a sampling frequency of 50 kHz and a signal-to-noise ratio of 39.5 dB [3]. Special care was taken to maintain the same microphone position, the posture, and also the type of interaction with the patient. The suggested posture was, according to the normal procedures for a correct phonation, back and head straight and aligned with the chair. The microphone was positioned in a way to minimize the effect of room reverberation making an angle of 45° to the opposing wall. Another important issue was to maintain a fixed distance between the microphone and the patient's mouth, which can influence the amplitude of the captured signal or even provide undesirable resonances at specific frequencies. The direction is also relevant; a microphone directed to the mouth can capture a pressure wave that will cause an exaggerated excitation of the microphone. The distance and angle chosen was 15 cm and 45°.

Before each recording session, the volume level was calibrated to adapt the dynamic range of the input signal in order to prevent overload distortion and, at the same time, minimize the quantization error provided by the discrete and limited range of the A/D converter.

The new database was organized per patient and per date of exam. Each exam was saved in *wav* format with the filename according to the type of the exam and patient's reference number. The personal identification number of the patients was separated from the rest of the database for privacy reasons.

The DB02 database is still being acquired, and it currently comprises 22 speakers of which 8 had diagnosed larynx pathologies. For balancing reasons a subset of the database was also used in this case including all the diagnosed speakers and 8 randomly selected speakers with no diagnosed pathologies.

5. Pitch-Mark Detectors

The jitter estimation algorithms that we want to evaluate require the location of a fixed point in the glottal cycle, called a pitch-mark (PM). A good candidate for this reference point is the glottal closure instant (GCI) since it corresponds to a discontinuity in the glottal flow caused by the abrupt closure of the vocal folds, interrupting the passage of the air through the glottis. Since the residue signal resulting from the inverse filtering of the speech signal by the LPC filter is an approximation of the derivative of the glottal flow, the discontinuity in the flow produces large negative peaks. Normally these peaks fall slower than they recover, which can be explained by the vocal folds' closing/opening process. A regular vibration produces periodic peaks with fundamental frequency F0.

A common algorithm for the glottal closure instant detection is dypsa [14], for which there is an implementation in the VoiceBox toolbox [15].

We have implemented a modification to *dypsa* algorithm for sustained vowels, named *dymp*. This modification considers that the glottal closure instants, calculated by *dypsa*, are a first approximation of the real GCIs. Since we assume that the vocal tract is stable, instead of using time-varying LPC filter coefficients, we can try to locate the set of coefficients that produced the most prominent peaks in the residue. By analysing the residue resulting from the time-varying LPC filter we can locate the pair of pitch periods with the largest peaks and the corresponding set of filter coefficients. This best set of filter coefficients is then used to filter the whole sustained vowel producing a residue with more prominent peaks (Figure 1(b)) . The GCIs are then better located in this enhanced residue signal.

Table 1: Naming of the pitch marking tools.

Name	Summary
dymp	Pitch marks computed using dypsa with pitch-synchronous LPC coefficients
mdvp	Pitch marks computed with MDVP's peak-picking tool
praat	Pitch marks computed with Praat's cross-correlation tool

The results, when compared to advanced systems like Praat and MDVP, suggest a significant improvement, especially for irregular voices.

MDVP and Praat rely on pitch marks that do not coincide with the glottal closure instant. Praat uses a waveform-matching procedure, that locates the pitch marks where the best matching between wave shapes occurs using the "cross-correlation" maximum. On the other hand, MDVP uses a peak-picking procedure that locates the pitch marks on the local peaks of the waveform.

6. Jitter Models

For this study, three different models of jitter were used.

The first one considers that jitter is just a simple variation of period, which can be measured by subtracting each period of the pitch period sequence to its neighbour or combinations of its neighbours. This method usually assumes a long time periodicity that sometimes does not exist and provides a single measurement for the whole signal:

$$\text{Jitta} = \frac{1}{N-1}\sum_{k=1}^{N-1} |P_0(n+1) - P_0(n)|, \qquad (1)$$

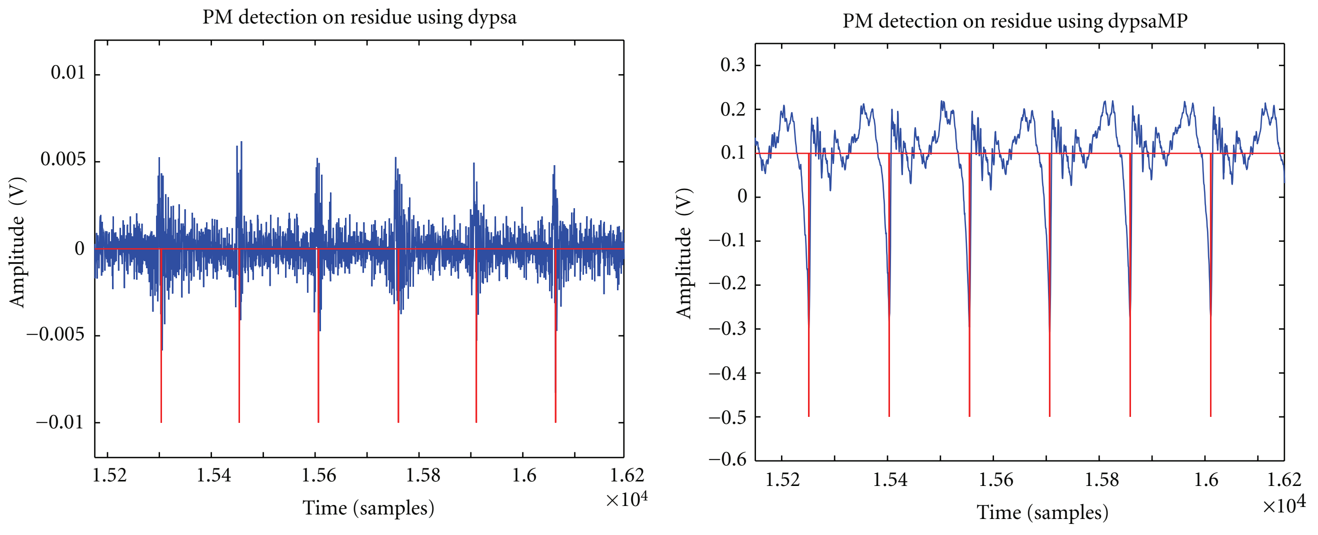
where $P_0(n)$ is the sequence of pitch periods lengths measured in microseconds.

The second model can be represented by a combination of two periodic phenomena on a long time range to achieve local aperiodicity behaviour in a short time range (Figure 2). If we assume a pulse like signal, it can be expressed as

$$s(n) = \sum_{k=-\infty}^{+\infty} \delta(n-2kP) + \sum_{k=-\infty}^{+\infty} \delta(n+\varepsilon-(2k+1)P). \qquad (2)$$

In this model, P is the average period and ε is a value that expresses the displacement of every other period, in a cyclic perturbation of a local constant value, occurring in every second impulse. The value of ε can range from 0, no jitter, to P, the average period length.

It is important to note that, for a direct comparison of the results, if we apply the first model to this second approach, the estimated jitter value is Jitta $= 2\varepsilon$. This factor comes from the assumption that in the first case Jitta is the direct subtraction of two periods, while for the latter ε is the half difference of the subtraction of two periods (Figure 2).



(a)

(b)

Figure 1: The residue signal resulting from the original dypsa algorithm (a) and from the proposed dypsaMP (b) .

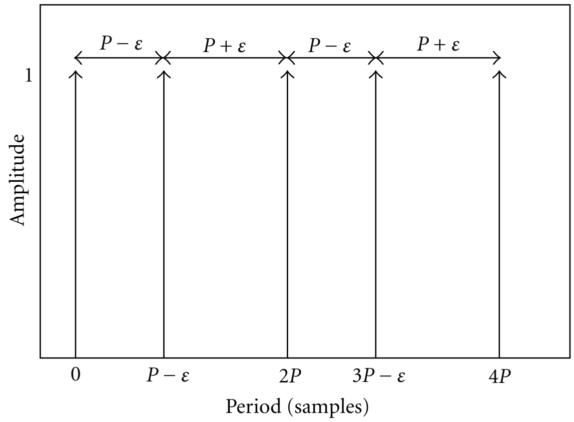


Figure 2: Example of a pitch period sequence with a local periodic and a local aperiodic component.

The major inconvenient of both of these models is the assumption that the underlying signal has a fixed fundamental frequency. However, apart for professional singers, many speakers do not have a total control on the whole process of phonation. Providing a regular glottal flow as well as a constant position of the vocal tract, while producing a regular vibration of the vocal folds, during recording period (normally 8 to10 seconds), is not achievable by all speakers. The amount of jitter determined by both previous methods depends on the ability of the speaker to hold a constant pitch. Slow monotonic changes in the fundamental frequency are considered as a period-to-period variation. In our view, only the nonmonotonic variation should be used as an indicator of the presence pathologies in the voice. For this reason we propose a third model allowing the glottal period to change linearly over time as shown in Figure 3. In this approach ε accounts only for the alternate change in period length, not including the effect of monotonic fundamental frequency variations.

The model can be expressed as

$$P_0(n) = P_0 + (n-1)\triangle_P + (-1)^n \varepsilon, \tag{3}$$

where Δ_P is the constant variation in the period length, ε represents the jitter value, and P_0 is the initial glottal period. Using 3 pitch mark instants $(P_0(1), P_0(2), P_0(3))$ it is possible to determine the 3 parameters of the model. With this short analysis window, it is sufficient to consider the linear approximation of the monotonic variation of the period.

This model assumes that the constant variation of period within the 3 period frame should not be considered pathologic jitter. The separation of both contributions is thought to be important to properly study real voices with or without fundamental frequency variations, leading to a more realistic measurement of local pathologic jitter. This third model is the base for a new method for jitter estimation.

7. Jitter Estimation Algorithms

7.1. The Jitt Algorithm (Used by MDVP and Praat). Both MDVP and Praat estimate the jitter value by computing the average absolute difference between consecutive periods (from the period sequence $P_0(n)$), divided by the average period expressed as a percentage:

$$\text{Jitt} = 100\frac{(1/(N-1))\sum_{k=1}^{N-1} |P_0(n+1) - P_0(n)|}{(1/N)\sum_{k=1}^{N} P_0(n)}. \tag{4}$$

This measure is commonly referred as percent jitter or relative jitter, while *Jitta* is the absolute jitter value expressed in microseconds. In MDVP this algorithm is named *Jitt*, while in Praat it is called Jitter *(Local)*. In this work we will use the MDVP name.

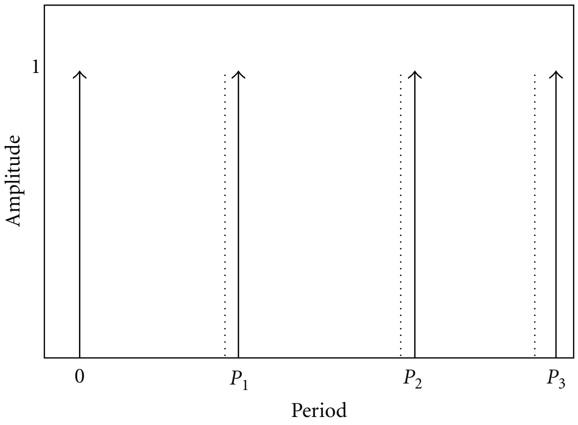


Figure 3: Example of a pitch period sequence with an increasing period.

We will also evaluate the average absolute difference between consecutive periods as expressed in (1), naming it by Jitta expressed in microseconds.

7.2. The STJE Algorithm. The Short Time Jitter Estimation (STJE) algorithm was proposed by Vasilakis and Stylianou [16], and it uses the second model for jitter mentioned above. The algorithm is based on mathematical attributes of the magnitude spectrum; the train of impulses can be separated in a harmonic part (H) and subharmonic part (S), where the subharmonic part is a direct result of the jitter effect:

$$|P(w)|^2 = H(\varepsilon, w) + S(\varepsilon, w). \tag{5}$$

When both spectra are represented in the same graph it can be proved that the number of crossings of both components is equal to the number of samples of jitter (ε) of the signal. This means that the minimum number of crossings in a graph of this type is also 0 (no jitter) and the maximum is P (the period length). An example of these plots can be seen later in this study (Figures 4 and 5).

The algorithm uses a sliding frame of 4P samples, which will slide P samples at the time to estimating a jitter value for each step. More details of implementation can be found in [6].

It is important to remind that this algorithm provides a sequence of local jitter estimations that does not depend on long-term periodicity, while Praat and MDVP provide a unique value due to expressions (3) and (4). To compare this result with the ones provided by MDVP or Praat, it is necessary to calculate the mean value of the sequence of local jitter estimations.

To analyse the performance of the STJE algorithm we used a synthetic voice produced using an all-pole filter to model the vocal tract. The filter coefficients were obtained by performing an LPC analysis on a sustained vowel produced by a male speaker, with a fundamental frequency of around 144 Hz, and using an analysis frame size of 4 glottal periods. As expected, the algorithm *STJE* was able to detect five intersections, corresponding to the exact jitter value introduced in the impulse train used as the filter excitation (Figure 4). For a more realistic result, the STJE algorithm was applied on two frames of a real voice using a window length of four periods. The first frame was carefully chosen in order to comply with the second jitter model while the second frame was chosen randomly. In both cases the jitter value was also manually estimated on the time signal using the Jitt algorithm and the results were compared. In the first case the STJE correctly estimated a jitter of 1 sample, but in the second one the estimated jitter was 5 samples while the manual estimation was 1 sample.

Figure 5 shows the power spectrum of both the harmonic and subharmonic components. The result shows an unexpected number of intersections, which increase jitter to values impossible to compare with MDVP's or Praat's. Several attempts to correct the intersection counting, such as changing the threshold for intersection validation, applying different pre-emphasis, or even displacing the middle of the analysis frame inside the period (to assure that it was not a PM detection problem), were taken into account, but no significant improvements were obtained.

One explanation for the higher than expected intersection count can be the lowpass characteristic of the voiced component of the speech signal that, when aspiration noise is present, it is masked in the high-frequency region of the spectrum. This adds additional crossings between the harmonic and sub-harmonic components not predicted by the model.

In conclusion, if the real voice follows the proposed jitter model, the algorithm estimates correct values. However, since natural human voices are quite irregular, only in a few cases STJE produces results comparable with MDVP or Praat.

7.3. The LocJitt Algorithm (Proposed). The proposed *LocJitt* algorithm aims to estimate the local jitter using the third model for jitter that was previously presented. The main goal is to provide a better jitter estimation by discarding monotonic variations in fundamental frequency that occurs in natural voices.

The algorithm uses a frame of length equal to 3 consecutive glottal cycles (4 Pitch Marks):

$$\begin{aligned} P_0(1) &= P_0 - \varepsilon, \\ P_0(2) &= P_0 + \Delta p + \varepsilon, \\ P_0(3) &= P_0 + 2\Delta p - \varepsilon, \end{aligned} \tag{6}$$

where P_0 is the length of the first glottal cycle excluding the jitter effect, $\triangle_P$ is the monotonic increment in the length of the glottal cycle occurring every period, and ε is cycle-to-cycle fluctuation caused by jitter. Using this set of equations it is easy to derive an expression to compute the jitter value using the length of 3 consecutive glottal cycles:

$$\varepsilon = \frac{1}{4}[(P_0(2) - P_0(1)) - (P_0(3) - P_0(2))]. \tag{7}$$

Like SJTE, this algorithm has the ability to compute a jitter estimate for every glottal cycle by shifting the analysis window by one glottal cycle.

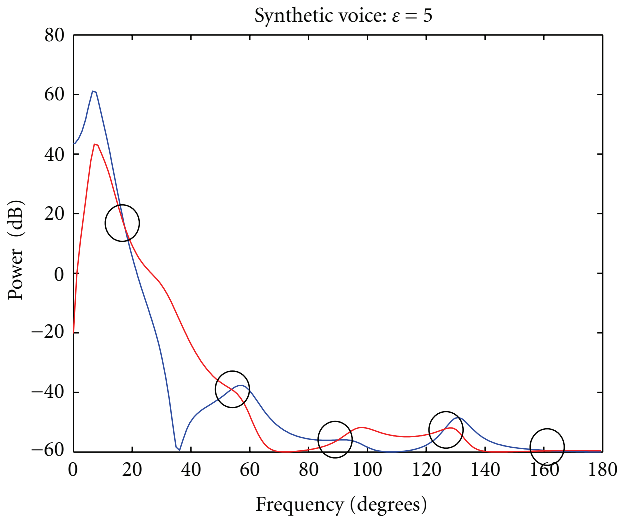


Figure 4: Power spectrum of harmonic and subharmonic parts of a synthetic signal. The jitter introduced ($\varepsilon = 5$ samples) corresponds to five crossings. No pre-emphasis was preformed.

Two versions of the algorithm were made: *LocJitt* produces an estimate of the local jitter as a percentage of the average glottal period, and *LocJitta* estimates the absolute value of the local jitter expressed in microseconds.

To evaluate the effect of these slower variations on the fundamental frequency on the jitter estimation computed using the *Jitt* algorithm used by MDVP and Pratt, we will assume that the pitch period sequence is given by (2) with fixed values for ε_i and $\triangle_P$ Using (4) it can easily be shown that for an even number of periods if the amount of jitter is larger than the slow varying changes in the pitch period, the Jitta algorithm estimates the correct value for ε:

$$2\varepsilon > \Delta p \longrightarrow \text{Jitta} = 2\varepsilon. \tag{8}$$

However, for small jitter values when compared with the slow variations of the glottal period, the Jitta algorithm estimates not ε but the slow variation:

$$2\varepsilon < \Delta p \longrightarrow \text{Jitta} = \Delta p. \tag{9}$$

The proposed *LocJitta* algorithm does not have this problem and correctly separates the estimate of ε from the value of $\triangle_P$.

This difference is most important in the cases where jitter is present but with a small value, when it is most difficult to detect. Also, localized variations in fundamental frequency that went undetected during the voice acquisition procedure can result in erroneous jitter estimation.

8. Evaluation of Jiiter Algorithms for Pathological Voice Detection

As we saw earlier, each algorithm for jitter estimation is based on its own model of jitter. It is thus hard to compare the results on real voices since each algorithm is, in effect, measuring a different thing. The best way to evaluate the different algorithms is on their ability to perform a certain task. In our case we decided to compare the algorithms in their capability of detecting a pathologic voice. This way, we are not interested in their ability of providing a good estimate on the amount of irregularity of the glottal cycles but only if they can discriminate the irregularities that correspond to pathological conditions as opposed to the normal aperiodicity observed in natural voices.

Table 2: Naming of the jitter estimation algorithms.

Name	Summary
Jitt	Global estimation based on the average difference in period length
STJE	Local estimation based on the difference in length of every 2 periods
LocJitt	Local estimation based on the non-monotonic difference in period length

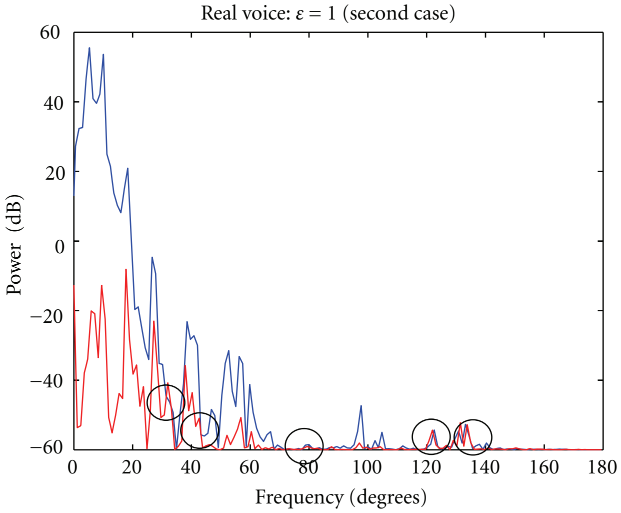


Figure 5: Power spectrum of harmonic and subharmonic parts of a real voice. The jitter measured on the time signal was 1 sample but the STJE algorithm counted 5 crossings.

For this purpose, two databases were analysed, the MEEI databases, provided by KayPENTAX, and the database DB02 created for this study and presented earlier.

The goals of the analysis were first, to test if each algorithm was good enough to be used by itself to distinct pathologic from normal voices, and second, to find out which algorithm had the best performance for such task.

To evaluate both the pitch marking methodology and the jitter estimation algorithm a set of 14 tools were created:

(i) dympSTJE: STJE based on dypsaMP's pitch marks, jitter measured as a percentage of the period,

(ii) dympSTJEa: same as previous but with jitter measured as an absolut value in microseconds,

(iii) dympJitt: Jitt based on dypsaMP's pitch marks, jitter measured as a percentage of the period,

(iv) dympJitta: same as previous but with jitter measured as an absolute value in microseconds,

(v) dympLocJitt: LocJitt based on dypsaMP's pitch marks, jitter measured as a percentage of the period,

(vi) dymp*LocJitta*: same as previous but with jitter measured as an absolut value in microseconds,

(vii) mdvpJitt: Jitt using MDVP's pitch marks, jitter measured as a percentage of the period,

(viii) mdvpJitta: same as previous but with jitter measured as an absolut value in microseconds,

(ix) mdvpLocJitt: LocJitt using MDVP's pitch marks, jitter measured as a percentage of the period,

(x) mdvp*LocJitta*: same as previous but with jitter measured as an absolute value in microseconds,

(xi) praatJitt: Jitt using MDVP's pitch marks, jitter measured as a percentage of the period,

(xii) praatJitta: same as previous but with jitter measured as an absolut value in microseconds,

(xiii) praatLocJitt: LocJitt using Praat's pitch marks, jitter measured as a percentage of the period,

(xiv) praat*LocJitta*: same as previous but with jitter measured as an absolute value in microseconds.

The preliminary results with the STJE algorithm showed that, when compared with other methods, it has a reduced dependency on the pitch marking tool being used. This is because the algorithm is based on spectral analysis, while the remaining methods are temporalbased. These results, together with the computational complexity of the algorithm, justify its use only in conjunction with the pitch marking tool dymp.

8.1. Decision Threshold. All the tools provided their own estimate on the amount of jitter in the input signal. Since we require a binary decision regarding the possibility of the voice being pathological or not, a decision threshold must be found for each tool.

To tune the thresholds we have used a group of 50 pathological and 50 normal voices randomly selected from the MEEI data set presented earlier. Since some data was sampled at 25 kHz and some at 50 kHz, we decided to start by converting all voices to 25 kHz and then to oversample them to 44.1 kHz. In order to avoid overtraining, the data set was divided into 10 randomly chosen groups with five pathologic and five nonpathologic voices each. A 10-fold cross-validation was then preformed, where, in each fold, the threshold was selected based on nine of these groups (a total of 40 samples), but its performance was evaluated on the remaining group of 10 voices. By rotating the left-out group, ten tests were conducted and the results are presented in Table 3. The mean accuracy is the average of the percentage of correct pathological/nonpathological voice decisions for each fold. The variance of the 10 results is also presented. This table shows that the different tools provide different estimates for jitter not only because they rely on different models for jitter but also because the results are based on different pitch marking methods. This can explain, for example, the difference between the threshold from *dympJitt* and *mdvpJitt*, or between *dympLocJitt* and *dympSTJE.*

Table 3: Results of the 10-fold cross validation procedure. The mdvpLocJitta tool produced the better average accuracy with a low variance on the 10 tests.

	Mean accuracy	Variance	Threshold
dympSTJE	76%	2%	3.44%
dympJitt	68%	2%	0.72%
dympLocJitt	68%	2%	0.66%
mdvpJitt	70%	0%	0.44%
mdvpLocJitt	70%	0%	0.40%
praatJitt	78%	3%	0.15%
praatLocJitt	74%	2%	0.12%
dympSTJEa	81%	2%	250.1 μs
dympJitta	70%	1%	46.1 μs
dymp*LocJitta*	71%	1%	60.9 μs
mdvpJitta	82%	1%	19.1 μs
mdvp*LocJitta*	84%	1%	19.6 μs
praatJitta	80%	2%	8.6 μs
praat*LocJitta*	79%	2%	7.4 μs

The results of the 10-fold cross validation procedure were used to calculate the best decision threshold for each tool. The values are also presented in Table 3.

8.2. Tool Evaluation. After the definition of the best thresholds for pathological/nonpathological voice classifier, the different tools were evaluated in the two previously described database: the subset of the MEEI and DB02.

On the selected subset of the MEEI database, the tools showed a similar behaviour to what was observed in the 10-fold cross validation test: the best PM locator is the MDVP software. Regarding the jitter estimation tool, the STJE algorithm performed better than the remaining tools. Comparing this result with the 10-fold test, it is clear that the larger variability of values that this algorithm produces makes it more dependent on the size of the data, that is, used to tune the threshold. Except for the case of pitch marks produced by the Praat tool, the new LocJitt algorithm performed equal to or better than the common Jitt measure.

Another interesting result is the better performance of absolute jitter values (measured in microsecond) over relative ones (measured in %) of the glottal period sequence. This observation suggests that there is a certain amount of aperiodicity that seems to indicate the presence of a pathology, that is, independent of the length of the glottal cycle. The use of relative jitter measures can prevent the detection of a pathology when the voice has a very low fundamental frequency, that would be detected with an absolute jitter measurement. Finally, the STJE algorithm seems to present a good accuracy, although it provides much higher thresholds combined with a rather low robustness (defined by a larger variance).

To see how the tools behaved in a completely different databases we also performed the evaluation on the DB02 database. This database, although smaller, had the advantage

Table 4: Results of the evaluation on the full databases.

	MEEI	DB02
dympSTJE	83%	69%
dympJitt	71%	88%
dympLocJitt	71%	88%
mdvpJitt	73%	63%
mdvpLocJitt	75%	63%
praatJitt	80%	69%
praat*LocJitt*	77%	69%
dympSTJEa	87%	69%
dympJitta	75%	88%
dymp*LocJitta*	76%	88%
mdvpJitta	84%	63%
mdvp*LocJitta*	85%	63%
praatJitta	82%	69%
praat*LocJitta*	82%	69%

of not being used in the threshold tuning process, plus, it was recorded in a completely different environment. Table 4 presents interesting results when compared to the previous ones. A general analysis shows that the results for this database are quite different. Firstly, STJE performance decreases, probably explained by the fact that these voices were recorded with a much higher sampling frequency, containing also more noise, which will increase the probability of intersections in the frequency domain.

Secondly, tools using mdvp's PM seem also to provide lower accuracies on the new Database. It is a fact that MDVP is sensitive to noise, which may probably influence the localization of the Pitch Marks, conditioning the final Jitter estimation. On the other hand, Praat seems to present, for a noisy environment, more accurate results; this fact is also described in literature [6].

For evaluation on DB02, the best performance goes for the tools using the *dymp* pitch marking tool. Due to the low number of voices in this database, it is assumed acceptable the fact that no differences between *Jitt* and *LocJitt* algorithms are detected. Also, in this database, there were no noticeable differences in performance of absolute jitter values over relative ones. This can be explained by the smaller size of this database and by the fact that it was recorded at a higher sampling rate (50 kHz).

All results, although preliminary, provide a very important conclusion that the jitter seems to be in fact an important measurement to indicate the existence of a possible pathology of the vocal folds.

9. Conclusions and Future Work

The first conclusion is that although most previous results use relative jitter values, in our study on the MEEI database absolute jitter values produced better results in the detection of pathological voices. This difference was not observed in the DB02 which can be explained by the smaller size of this database. It was expected that the amount of the disorder (expressed by the parameter jitter) would depend directly on the frequency of vibration of the vocal folds, but the results suggest a different conclusion: the jitter threshold for pathological voice seems to be independent of the period length. In a future work we plan to extend this study, analysing sustained vowels of the same speaker with a higher and a lower pitch to see the influence of the fundamental frequency on jitter measurements.

The *dymp* pitch marking tool, when applied to nonideal conditions or to higher sampling frequencies, produced the best performance. The inverse filtering technique is a promising solution for clinical applications, where normally it is difficult to provide an ideal acoustic environment.

Concerning the new proposed measure for jitter, *LocJitt*, it provided the highest accuracy and the minimum variance, during the parameter tuning process. In the evaluation on the full database the best results for the MEEI database were achieved with the STJE algorithm; however, the result seems to be dependent on the database since it did not performed as well on the DB02. The only case when Jitt outperforms LocJitt is when the pitchmarks are computed with the Praat tool and when using relative jitter. In all other cases and for both databases LocJitt achieved results that are equal to or better than Jitt.

An interesting future work would be to continue the recordings of the DB02 database in order to have a significant number of entries to better adjust threshold levels, not only for an individual jitter evaluation but also for more complex evaluation where jitter is one of several features to detect perturbations in voice.

At last, the database DB02 also include other exams, like the sustained vowel with increasing pitch, the text reading, or even the AEIOU exam, that were not yet used. We hope that further research on these exams will bring useful information about the effect of the different pathologies in the mode of vibration of the vocal folds.

As final conclusion, we would to reinforce that the objective measures of voice quality resulting from acoustic analysis can be a very powerful tool, not just for pathological voice detection but also for other domains like voice-therapy or even professional voice coaching. The joint effort of physicians and engineers should be targeted not only in finding voice disorders but, most importantly, in preventing them.

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