VOICE SIGNALS CHARACTERIZATION THROUGH ENTROPY MEASURES

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Keywords: Voice, entropy, phase space reconstruction, nodule, predictability.

Abstract: Human voice has been a matter of interest for different areas as technological development and medical sciences. In order to understand the dynamic complexity of healthy and pathologic voice, researchers have developed tools and methods for analysis. Recently nonlinear dynamics has shown the possibility to explore the dynamic nature of voice signals from a different point of view. The purpose of this paper is to apply entropy measures and phase space reconstruction technique to characterize healthy and nodule affected voices. Two groups of samples were used, one from healthy individuals and the other from people with nodule in the vocal fold. They are recordings of sustained vowel /a/ from Brazilian Portuguese. The paper shows that nonlinear dynamical methods seem to be a suitable technique for voice signal analysis, due to the chaotic component of the human voice. Since the nodule pathology is characterized by an increase in the signal's complexity and unpredictability, measures of entropy are well suited due to its sensibility to uncertainty. The results showed that the nodule group had a higher entropy values. This suggests that these techniques may improve and complement the recent voice analysis methods available for clinicians.

1 INTRODUCTION

The human voice is one of the principal means of communication, and the acoustic signal carries significant information about some individual characteristics. The complex normal or pathologic voice production mechanism involves different variables. Vocal fold biomechanics in association with aerodynamic variables play an important role in voice production and they are linked to the voice quality changes.

In order to study normal voice and the different voice disorders, scientists from diverse areas developed several methods and tools for measurement, diagnosis and voice treatment. Therefore traditional acoustic analysis is an essential and familiar tool for physicians and speech therapists.

Traditionally, voice has been modeled as a linear process and acoustic analysis tools are based in linear system theory. Acoustic parameters evaluate perturbation or noise contents in the voice signal. The classical perturbation parameters evaluate jitter (fundamental frequency variation), and shimmer (amplitude variation). Two parameters used to determine the voice signal noise quantity are the deterministic Harmonic to Noise Ratio (HNR) and the Coefficient of Excess (EX) that evaluate the noise from a statistical point of view (Davis, 1979).

Another interesting parameter is the pitch amplitude (PA), which is a normalized measure of the amplitude of the pitch period peak of the residue signal autocorrelation function. It has a high value for healthy vowel signals that have clearly defined pitch period. However, for breathy pathological voices, the PA is low because the signals have weak periodicity (Davis, 1979).

Although, these linear tools have been used over the years, they are based in the assumption that voice is a linear phenomenon. But, voice production is a complex mechanism that involves different variables and exhibits nonlinearities (Kumar and Mullick, 1996). Considering human voice production (healthy and pathologic) as a nonlinear system, it can be described by a number of observable output states. Therefore it can be used in the construction of a state

Rogério Scalassara P., Eugenia Dajer M., Dias Maciel C. and Carlos Pereira J. (2008).
VOICE SIGNALS CHARACTERIZATION THROUGH ENTROPY MEASURES.
In *Proceedings of the First International Conference on Bio-inspired Systems and Signal Processing*, pages 163-170
DOI: 10.5220/0001065401630170

space description of the system behavior. Voice signal, as a time series data, makes available the study of an underlying dynamic and provide the necessary information to obtain a reconstruction of the state space behavior of the system. Thus, phase space reconstruction technique can be used for voice characterization.

Nowadays, the use of entropy measures is widespread in many fields of science, whether applied to stochastic processes or dynamical systems. As presented by (Amigó et al., 2007), the application of entropy to discrete phase space is very natural, since its concept has been extended from deterministic continuous dynamics to stationary random processes and discrete dynamical systems. (Amigó et al., 2007) present a quantity called discrete entropy to deal with finite-state systems. This quantity asymptotically converges to conventional entropy, as evidenced by several examples.

As an example of the applicability of entropy, (Kirk and Jenkins, 2004) show that the Kolmogorov entropy is used to investigate software metrics, allowing early assessment of the design quality of software project. Also, in (Lake et al., 2002), an entropy measure called sample entropy was proposed. The objective was to improve the diagnosis of neonatal sepsis by monitoring the heart rate characteristics. The rate variability is interpreted as changes in the complexity of the underlying physiological processes. Despite the fact the method showed sensitivity to other signal's parameters, the results were interesting and could be used for monitoring at-risk infants.

Measures of entropy are intimately related to the predictability of signals. These measures can be used to evaluate forecast skill of a system. According to (Kleeman, 2002), some progress has occurred in using processes ensemble spread as an indicator of predictability. This is formalized in a parameter called predictive power (Schneider and Griffies, 1999).

Natural processes seem to be unpredictable due to several reasons, as described in (Crutchfield and Feldman, 2003). The most important reasons are: unknown rules that govern the system, existence of intrinsic mechanisms that amplify fluctuations, observer-induced sources of randomness, insufficient volume of data, and, perhaps, the dynamics is too complicated to have predictions evaluated.

Since the presence of pathologies on the vocal folds results in behavior change of the voice production system, the produced signals are going to be less predictable than the healthy ones. This work aims to try to detect these changes using simple entropy measures to differentiate two kinds of signals: healthy and pathological. For this paper, the pathology studied is the presence of nodule in the vocal folds.

In Theory a brief description of the entropy estimation is presented and also an explanation about the vocal fold nodule pathology. In Materials and Methods the voice samples used in the study are described in some details. After that, the phase space reconstruction and entropy estimation methods are presented. Also, a small discussion is made about the voice samples' processing. In Results examples of signals' phase space analysis are shown with the general results of entropy measures. In Conclusion the final comments about the work is presented.

2 THEORY

In this section a brief explanation of the entropy theory is presented. Also, a description of vocal fold nodules is shown.

2.1 Entropy

According to (Cover and Thomas, 1991), entropy is a quantity defined for any probability distribution with properties that agree with the intuitive notion of information measures.

One of the entropy's first concepts was presented in (Shannon, 1948) as the definition of a measure of uncertainty of a random variable. Considering a random variable X that assumes values $x \in \chi$ where χ is a finite set, the entropy $H(X)$ can be defined by Equation (1), with units in bits.

$$H(X) = -\sum_{x \in \chi} p(x)\, log_2\, p(x) \tag{1}$$

The probability of x, $Pr\{X = x\}$, is denoted by $p(x)$. If $p(x) = 0$, $p(x)\, log_2\, p(x) = 0$ by convention. This quantity is dependent on the distribution of X instead of the actual values of the random variable. As discussed in (Crutchfield and Feldman, 2003), the entropy measures the average amount of bits necessary to store outcomes of the random variable.

2.2 Vocal Fold Nodules

Individuals with vocal nodules constitute a large part of the client population at voice clinics (Colton and Casper, 1996). They are commonly seen in women, children, salesmen, and teachers who have to use their voice too frequently. The main symptoms are hoarseness, breathiness, easy vocal fatigue, and throat discomfort. The voice is better in the morning and worsens in the afternoon after voice use (Fisher, 1996).

The vocal nodule is as a benign lesion occurring on both sides of the vocal folds, strictly symmetric on the border of the anterior and middle third of the vocal fold and usually immobile during phonation. The lesion is confined to the superficial layer of the *lamina propria* (Rosen and Murry, 2000; Hirano, 1991).

The vocal folds are subject to several forms of mechanical stress during phonation. Vocal fold vibration during phonation leads to impact stress during collision between the left and right vocal fold surfaces. According to different studies, nodules mostly occur at the midpoint of the membranous vocal folds, where impact forces are the largest and they are mostly bilateral (Titze, 1994; Jiang and Titze, 1994).

During the closing phase of the folds' vibration, the presence of nodules on the outer layer of vocal folds' tissue inhibits them from being completely folded on each other. Consequently the glottis closure is uncompleted, adding turbulent air to the voice signal. In order to reduce this effect, the subject increases the muscle tension and the subglottal pressure, consequently rising the vocal fold collision forces (Hillman et al., 1990).

Nodule voice shows perceptually strained/pressed voice quality and breathiness with various degrees of turbulent noise. Frequently, the voice also presents vibrations irregularities, such as roughness and instability, as well as vocal fry/creak (Hammarberg, 1998).

The nodules are responsible for pitch frequency and air flow volume changes, also amplitude and mucosal wave reduction and the noise-like turbulence of airflow in the vocal folds. This is mainly due to the incomplete closure of the vocal folds, glottal air leakage, and their asymmetrical vibration because of their biomechanical parameter alterations (Hugh-Munier et al., 1997).

3 MATERIALS AND METHODS

In this section the voice samples are addressed showing the groups and acquisition method. After that, the phase space reconstruction technique and the entropy estimation method are presented. Finally, the voice signals' analysis method is shown.

3.1 Voice Samples

For this study, 28 voice signals divided in two equal groups were used. The first group was composed of healthy people with no voice complaints or laryngeal pathology. The second group was composed of people with vocal fold nodules in different stages of disease evolution according to (Scalassara et al., 2007). These voice signals are part of a voice database of the Group of Bioengineering of the School of Engineering of São Carlos at the University of São Paulo, Brazil. These signals were collected along the past ten years and used in several studies (Rosa et al., 2000; Dajer et al., 2005).

All volunteers were diagnosed by physicians of the Otolaryngology sector and the Head and Neck Surgery sector of the Clinical Hospital in the Faculty of Medicine at Ribeirão Preto, Brazil (`http://www.hcrp.fmrp.usp.br`) by means of video-laryngoscope and stroboscope light.

The data recording was performed using a protocol similar to the one presented in (Uloza et al., 2005). The subjects were asked to produce a sustained vowel /a/ at a comfortable pitch and loudness level for about 3 seconds. The used microphone was in accordance to the standards established in Brazil. It was placed at a distance of 5 cm from the person's mouth. Consecutive trials were performed, selecting the signal with less voice variability.

As presented in (Davis, 1979), vowel sounds are generally used in studies of pathological speech because the vocal folds are vibrating during vowel phonation. Also, acoustics assessment of laryngeal function relates to adequacy of sustained vocal fold vibration. Therefore, in order to collect the data, the sustained /a/ phoneme was used to evaluate the acoustical parameters of the samples. In English, this phoneme is equivalent to "a" in "dogma".

At voice acquisition, it was necessary to check if the individual could cope with the phonation interval and, in negative case, he was asked to stop uttering. This procedure was important because the maintenance of the utterance causes an increase of the voice fundamental frequency and an artificial stability on its production (Rosa et al., 2000). In order to avoid the influence of transitory phenomena, the start and ending of the acquired voice signal were discarded. Then, it was possible to ensure that the beginning and ending of voicing did not influence the final result.

After that, the amplitude of the signal was normalized according to its absolute maximum value. It was necessary to eliminate the influence of different sound levels from the signals collected. All voices samples were quantized in amplitude with 16 bits and recorded in mono-channel WAV format to preserve the fidelity of the signal. The sampling frequency was 22050 Hz.

3.2 Phase Space Reconstruction Technique

In order to describe the nonlinear dynamic characteristics of voice signals, sustained vowel data set was analyzed with ANL (*Análise Não-Linear*) software

(Dajer et al., 2005). This piece of software was developed using Matlab 7.0 and the Tisean Package (Hegger et al., 1999; Kantz and Schreiber, 2004). The ANL is based in the phase space reconstruction technique and represent the vocal folds vibration as an orbit trajectory in phase space with time evolution.

The voice signal can be represented by the time series $x(t_i)$, $t_i = t_0 + iT$, with $i = 1, 2, \ldots, N$, where N is the length of the signal and T is the sampling period (Rabiner and Schafer, 1978). The phase space reconstruction of this signal is performed by plotting the time series $x(t_i)$ against itself at some time delay (Ott et al., 1994; Packard et al., 1980).

In order to create the reconstructed space for the time series $x(t_i)$, the method of delays is used (Fraser and Swinney, 1986; Hegger et al., 1999). A set of m vectors, called the embedding space, are formed from time delayed values of $x(t_i)$, Equation (2). In this set, m is the embedding dimension and τ is the time delay.

$$X(t_i) = \{x(t_i), x(t_i - \tau), \ldots, x(t_i - (m-1)\tau)\} \quad (2)$$

When $m > 2D + 1$, where D is the Hausdorff dimension, the reconstructed phase space is topologically equivalent to the original phase space (Fraser and Swinney, 1986). The delay τ is obtained by the first local minimum of the mutual information function of the signal (Fraser and Swinney, 1986).

3.3 Entropy Estimation

In order to estimate the signal entropy, an algorithm was developed based on the one presented in (Moddemeijer, 1989) with the optimizations shown in (Moddemeijer, 1999). The method is based on a simple histogram algorithm with bias correction and minimum mean square error estimation. In the cited paper, the author presents several examples that evaluate the algorithm showing its reliability.

The principle of the method is to try to estimate the probability distribution function (PDF) of the signal under study. This is performed by dividing the function in a rectangular grid with I equally Δx-sized cells. The occurrences of the signal's points in each cell, k_i, are summed. Then, the probabilities of each cell, p_i, is replaced by the estimative k_i/N, where N is the total number of samples of the signal. Therefore, the entropy estimator of Equation (3) is obtained, since the logarithms have base 2, the units are in bits. The bias correction for this estimator for discrete systems is given in Equation (4).

$$\hat{H}_x = -\sum_i \left(\frac{k_i}{N} log_2 \frac{k_i}{N} \right) + log_2 \Delta x \quad (3)$$

$$E\{\hat{H}_x\} \approx H_x - \frac{I-1}{2N} \quad (4)$$

An example of the use of this algorithm is now shown. It is taken from R. Moddemeijer website: `http://www.cs.rug.nl/~rudy/matlab/doc/entropy.html`. A normal distributed random noise is generated with zero mean and unity standard deviation. The signal and its histogram, obtained using 30 bins, are presented in Figures 1 and 2 respectively. The expected entropy of this signal is 1.4189 nat. Using the estimator the result is 1.3643, what gives an error of 3.85%.

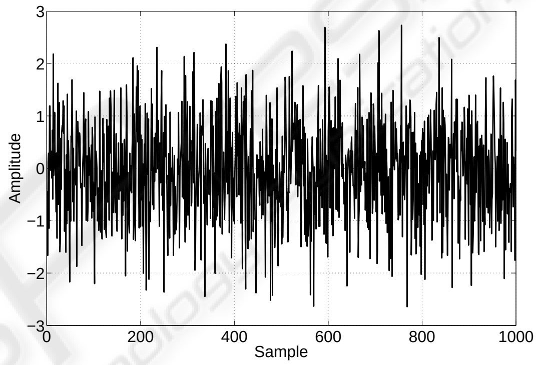

Figure 1: Signal of a normal distributed random noise generated with zero mean and unity standard deviation used to illustrate the entropy algorithm.

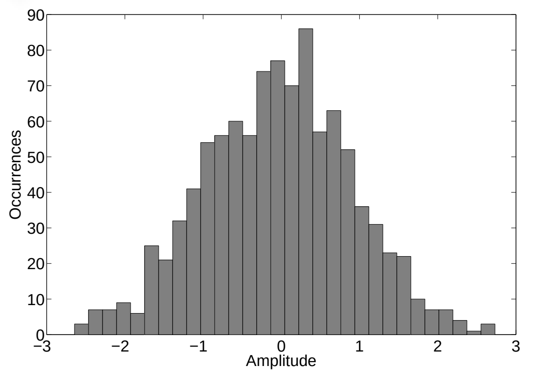

Figure 2: Histogram of the random noise signal used to illustrate the entropy algorithm. This histogram was obtained using 30 bins.

3.4 Analysis Method

Each voice sample was analyzed by a speech therapist and had its most stationary part selected. This stationarity was further analyzed by checking the result's power spectrum density (PSD), verifying if only minor changes occur. This is a simple form of obtaining wide sense stationary (WSS) signals (Hayes, 1996).

For all the samples, this procedure resulted in at least one second of voice sample. The result was divided in parts with length of 1000 points (approximately 50 milliseconds). Each of these signals were normalized by the absolute of its maximum value.

The PDF of these normalized signals were estimated according to the proposed method in order to evaluate their entropy. Since each signal has the same length and amplitude range, the entropy estimator does not favor any of them. The analysis is perfomed with the mean and standard deviations values of the signal's entropies.

4 RESULTS

Healthy and nodule voice samples analyzed by means of phase space reconstruction technique with ANL showed different visual patterns for each group.

In order to determinate the visual pattern characteristics, three kind of orbits' dynamic behavior were observed: a) number of loops, b) attractor course regularity, and c) attractor trajectories distribution (divergence and convergence of attractor orbits' trajectories).

For healthy voice signals, phase space reconstruction for sustained vowel /a/ presents a typical visual pattern. First, it is characterized by many concentric loops of different dimensions. The orbits' loops are correlated to the interaction between the fundamental frequency (F_0) and the harmonic frequencies (F_1, F_2, F_3, ...) of the signal. This configuration links the voice signal complexity and the number of harmonic frequencies amplified and contained in sustained /a/ vowel. Second, the attractor course is flat and regular and, third, the attractor trajectories are very close to each other showing convergence tendency.

Figure 3 shows a typical healthy voice signal of a sustained vowel /a/. Figure 4 shows its phase space reconstruction with time delay τ according to (Fraser and Swinney, 1986).

For nodule voice signals, phase space reconstruction of sustained vowel /a/ presents different patterns. In general, the nodule's pattern is characterized firstly by a single and irregular orbit loop differing from the healthy ones. Although the harmonic components are present in the glottal pulse, the higher muscle tension and subglottal pressure unbalance the (F_0)/harmonic frequencies ratio and the compensatory vocal tract gesture contributes to atenuate the harmonic frequencies, consequently producing a single trajectory loop.

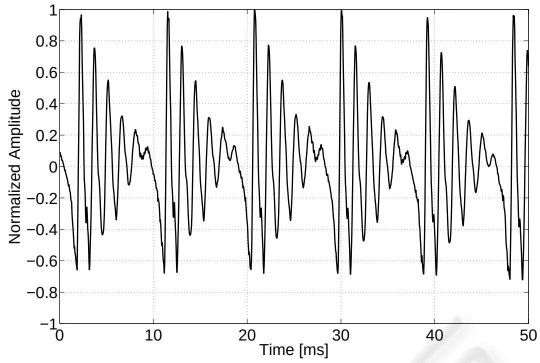

Figure 3: Example of a typical healthy voice signal of a sustained vowel /a/.

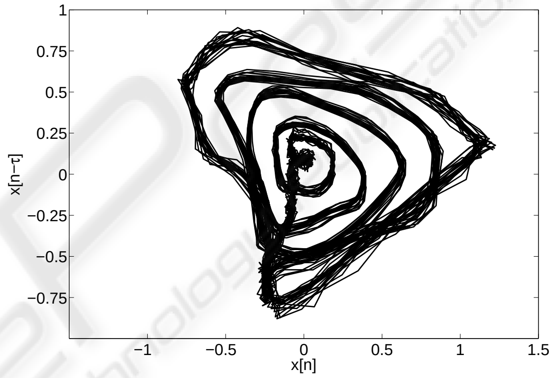

Figure 4: Phase space reconstruction of the typical healthy voice signal of a sustained vowel /a/.

Secondly, the attractor course is irregular and curly because of the incomplete closure of the vocal folds, turbulence of airflow and the asymmetrical vibration. Thirdly, the attractor trajectories present a disperse tendency caused by air flow volume changes and the mucosal wave variation. This irregularity can happen in some specific regions or even in different regions of the orbits.

Figure 5 shows a typical nodule voice signal of a sustained vowel /a/. Figure 6 shows its phase space reconstruction with time delay τ according to (Fraser and Swinney, 1986).

After the proper stationary regions of the signals were selected using the perceptual acoustic analysis and study of the phase space, the entropy estimations were performed. Since these selected samples had at least one second of voice, they were decomposed in 20 signals of 1000 points each. Figure 7 presents the mean and standard deviation entropy values of the results of these 20 signals for each of the 14 healthy and 14 nodule voice samples. These samples are ordered by their evaluation, therefore they are not paired.

As can be seen in the figure, the mean values of

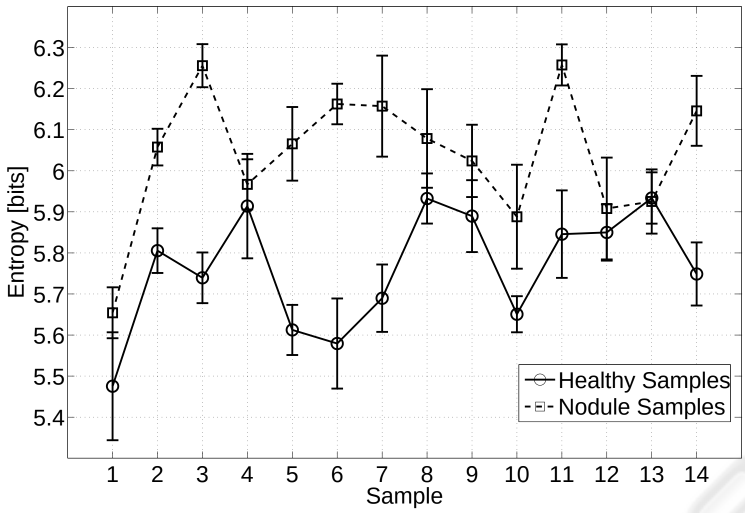

Figure 7: Entropy estimation results for the two groups of voice signals, healthy and nodule affected, each with 14 samples. Every point is a mean (with standard deviation) of entropy values of 20 signals (50 milliseconds each). The nodule group presented higher values than the healthy group, 99.75% probability in a Student-t test (significance level of 5%).

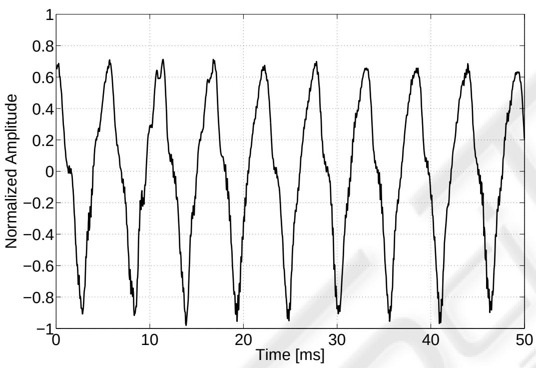

Figure 5: Example of a typical nodule voice signal of a sustained vowel /a/.

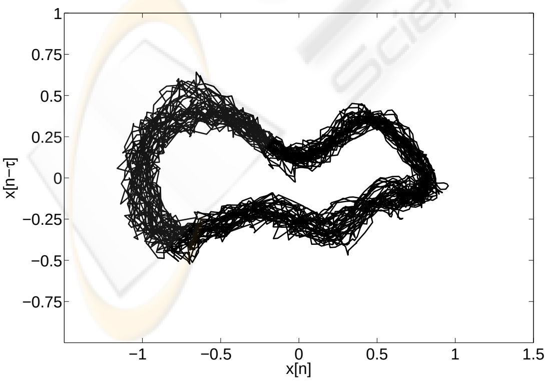

Figure 6: Phase space reconstruction of the typical nodule voice signal of a sustained vowel /a/.

the nodule samples seem to be higher than that of the healthy samples. According to the standard deviation values, the two classes seem to be separated. The mean entropy value of the healthy group is 5.76 bits with standard error of 0.14 bits, while the mean and standard error values of the nodule group is 6.04 and 0.16 respectively. The individual values obtained for these samples are shown in Table 1. An unpaired Student-t test with a significance level of 5% was performed on the data. It shows that the mean of the nodule group is indeed higher than that of the healthy group with a probability of 99.75%.

Table 1: Mean and standard deviation (Std) of the entropy values, in bits, of the results of the 20 signals of each of the 14 healthy and 14 nodule voice samples.

Healthy Samples		**Nodule Samples**	
Mean	Std	Mean	Std
5.48	0.13	5.65	0.06
5.81	0.05	6.06	0.04
5.74	0.06	6.26	0.05
5.91	0.13	5.97	0.06
5.61	0.06	6.07	0.09
5.58	0.11	6.16	0.05
5.69	0.08	6.16	0.12
5.93	0.06	6.08	0.12
5.89	0.09	6.02	0.09
5.66	0.04	5.89	0.13
5.85	0.11	6.26	0.05
5.85	0.07	5.91	0.12
5.93	0.06	5.93	0.08
5.75	0.08	6.15	0.09

Table 2: Mean values and standard deviations of jitter, shimmer and pitch amplitude (PA) for the signals under analysis (percentual values).

Samples	Jitter	Shimmer	PA
Healthy	0.47 ± 0.39	3.34 ± 0.88	54 ± 12
Nodule	3.37 ± 3.22	10.04 ± 4.74	36 ± 15

In order to compare the performance of the proposed method, the voice signals were analyzed aiming to extract vocal acoustic parameters. This was performed by a commercial software called *Análise de Voz* (Voice Analysis) version 6.0. The mean values (and standard deviations) of jitter, shimmer and pitch amplitude (PA) over the 14 samples of each group of signals are presented in Table 2.

The jitter and shimmer mean values are smaller for the healthy group, as expected, and present narrow probability distribution. For the nodule group the distribution is much wider. This variation can be interpreted as an increase of the uncertainty of these signals. The mean PA is higher for the healthy group because the signals have a more defined period, the cause of the smaller jitter values.

The higher variability of the parameters for the nodule group is probably due to physiological differences among the occurences of the pathology. Nodules can be manifested in several ways along the vocal folds, some layers of tissue may be modified or not. Therefore, the system dynamic alterations can lead to much different voice signals. It is interesting to observe that the presented parameters compare favorably to the results obtained by the entropy method.

5 CONCLUSIONS

In this work, there was an attempt to look into voice as a dynamical signal and, consequently, explore new processing techniques for healthy and vocal nodule's voice signals. A practical application and advantages of dynamical analysis were also presented. Thus, we believe that nonlinear dynamics tools, as entropy measures and phase space reconstruction, may help in a review of many of the voice dynamic characteristics.

We presented a study of the use of entropy measures to two groups of voice signals. They were composed by samples of healthy and nodule in the vocal folds affected individuals. The samples were analyzed by a speech therapist with aid of phase space plots. The most stationary parts of these signals (in the WSS sense) were selected. The entropy method developed by (Moddemeijer, 1989) was used to estimate the entropy of samples of 50 milliseconds of each of the signals. The results obtained for the mean and standard deviation values were tested with a Student-t test being clearly separable. This is an indication of the behavior of the entropy of nodule signals, at least in the voice samples studied.

The nodule group showed a higher entropy value than the healthy group. This was expected because this vocal fold pathology is characterized by increase of the signal's complexity (Hammarberg, 1998; Hillman et al., 1990). This effect is reflected in an increase of the uncertainty of the signal, that is, the signal becomes less predictable (Crutchfield and Feldman, 2003; Schneider and Griffies, 1999).

The results were compared to jitter, shimmer and pitch amplitude values of the samples, which were obtained with a commercial software. The variability of the parameters for the nodule affected group was significantly higher than that of the healthy group, therefore presenting a behavior that compares favorably to that obtained with the entropy method.

This work is still an initial study, but phase space analysis helps to depict the vowel pattern in a dynamical way. This technique allows to visualize the differential dynamics between healthy voices and voices with vocal folds nodules. Future works intend to use predictability measures to improve the understanding of the relation of pathologies with the complexity of the voice signal. Also, measures applied directly to the phase space of the signals are planned as well.

ACKNOWLEDGEMENTS

The authors acknowledge the Research Foundation of the State of São Paulo (FAPESP) and the Program of Students - Post-graduation Agreement (PEC-PG) for the support and scholarship. We also thank the School of Engineering of São Carlos (EESC/USP) for the research facilities and the use of its voice database.

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