Clustering Pathologic Voice with Kohonen SOM and Hierarchical Clustering

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Abstract: The main purpose of clustering voice pathologies is the attempt to form large groups of subjects with similar pathologies to be used with Deep-Learning. This paper focuses on applying Kohonen's Self-Organizing Maps and Hierarchical Clustering to investigate how these methods behave in the clustering procedure of voice samples by means of the parameters absolute jitter, relative jitter, absolute shimmer, relative shimmer, HNR, NHR and Autocorrelation. For this, a comparison is made between the speech samples of the Control group of subjects, the Hyper-functional Dysphonia and Vocal Folds Paralysis pathologies groups of subjects. As a result, the dataset was divided in two clusters, with no distinction between the pre-defined groups of pathologies. The result is aligned with previous result using statistical analysis.

1 INTRODUCTION

Pathologies related with the human phonation apparatus can affect the characteristics of the voice, and can be very limitative for the patients, depending on the pathology and its degree of evolution. Some pathologies impose serious limitation on voice and consequentially on daily living, in addition to causing serious damage on patient's health (Teixeira, Alves and Fernandes, 2020). Some of the most common pathologies are: Carcinoma, Chronic Laryngitis, Cysts, Granuloma, Intubation Granuloma, Hypopharyngeal Tumor, Laryngeal Tumor, Reinke's Edema, Vocal Fold Paralysis, Vocal Fold Polyps, Functional Dysphonia, Hyper-functional Dysphonia, Hypofunctional Dysphonia, Hypotonic Dysphonia and Psychogenic Dysphonia (Teixeira J. P., Fernandes, Teixeira F., Fernandes, 2018).

The traditional diagnostic exams can be very cumbersome and expensive for the patient.

Vocal acoustic analysis techniques can allow a screening test or pre-diagnose that can avoid the traditional exams to several patients. These techniques may also be used as a valuable tool for the otolaryngologist exam. In the area of rehabilitation, well-designed tools can be useful for the evaluation of the recover after the treatment.

Support decision system for voice pathologies diagnose and identification based on acoustic analysis have been under research recently as alternative to invasive technics like endoscopy, laryngoscopy and stroboscopic exams (Martínez, Lleida, Ortega, Miguel and Villalba, 2012), (Teixeira J. P., Fernandes, and Alves, 2017).

With this different approach we are able to do the classification between healthy or pathologic voices or even the identification of the pathology. Anyhow, the length of the available dataset for each voice pathology has shown as the bottleneck to use more sophisticated and powerful Deep Learning tools such as LSTM recurrent Deep Neural Networks (DNN), 1-D Convolutional DNN or transfer learning techniques, because of the higher dimension of the dataset required (Guedes, Junior, Teixeira F., Fernandes J. and Teixeira J. P, 2018), (Teixeira F., and Teixeira J. P., 2020). This paper intends to step forward searching the solution for the scarcity of the existent speech datasets to classify the pathology and not simply classify between healthy or control. The main idea is to cluster similar pathologies based on the traditional acoustic parameters used for voice

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pathologies in order to enlarge the dataset for some clustered pathologies (Fernandes J. *et al*, 2019).

Assessment of voice pathologies can be done by means of acoustic analysis of the voice signal, through the analysis of a set of parameters. In the literature review other speech parameters can be found like Energy, different order of moment, kurtosis and relations between energy bandwidths (Panek, Skalski, Gajda and Tadeusiewicz, 2015) and (Teixeira J. P., Fernandes, and Alves, 2017). Tsanas, Little, McSharry & Ramig (2010) used several order of Mel-Frequency Cepstrum Coefficients (MFCC), delta MFCC, ratio of the log transformed means (VFER-NSR), extend of turbulent noise (DFA) and several measures of Fundamental Frequency (F0) for Parkinson's disease symptoms severity.

In this work parameters such absolute jitter, relative jitter, absolute shimmer, relative shimmer, harmonic-to-noise ratio, noise-to-harmonic ratio, autocorrelation will be used as a reference (Felippe, Grillo and Grechi, 2006), (Finger, Cielo and Schwarz, 2009), (Teixeira J. P., and Fernandes P. O., 2014) and (Fernandes J. *et al*, 2019).

The aforementioned set of parameters, were used to apply clustering techniques that will contribute to the organization of data into groups by means of the similarity among the analyzed elements. Thus, samples that belong to the same set tend to be more similar than the rest of the elements formed by other sets (Jain, Murty and Flynn, 1999). To achieve clustering using an ANN, unsupervised learning is required. This means that the network receives no guidance, i.e., only the set of inputs is provided, there is no predefined output (Jain, Murty and Flynn, 1999), (Haykin, 1999), (Pavel, 2006).

In this work, clustering techniques will be applied in order to verify whether the dataset of voice features can be grouped based on the set of parameters previously referred. Kohonen's Self-Organizing Maps (SOM) and Hierarchical Clustering are the methods used in this work.

The section 2 of this document presents the materials used in the study, presenting the database, acoustic parameters and the clustering methods: SOM and hierarchical clustering. Sequentially, section 3 presents the results and discussions. Closing with the conclusions, presented in section 4.

2 MATERIALS AND METHODS

In this section the dataset will be presented, followed by the definition of the used parameters and the clustering methods, namely the Kohonen's Self Organizing Maps and Hierarchical Clustering.

2.1 Database

The Saarbruecken Voice Database (SVD) was used as the original speech dataset. It has a collection of speech recordings of over 2000 subjects pronouncing the sustained vowels /a/, /i/ and /u/ in low, normal, high, and low to high tone, plus a small sentence in German. The SVD is an open dataset of pathologic and healthy speech records provided by the Institute of Phonetics of the University of Saarland. All audios have a sampling frequency of 50 kHz and 16-bit resolution (Martínez, Lleida, Ortega, Miguel and Villalba, 2012), (Fernandes J. *et al*, 2019).

In this study, only the sustained vowel /a/ in normal tone was used because it presents a larger opening of the vocal tract compared to the other vowels. Besides, samples of the Control group, the Hyper-functional Dysphonia and Vocal Fold Paralysis pathologies were used. These two pathologies contains the largest number of subjects in the database. Table 1 displays the characterization of the used subset with 486 subjects.

2.2 Acoustic Parameters

The Praat software (Boersma P, Weenink D, n.a.) allowed the extraction of parameters used in acoustic analysis. By selecting the file from the SVD, it is possible to select the complete voice segment and extract the parameters: absolute jitter and shimmer, relative jitter and shimmer, HNR, NHR and autocorrelation (Teixeira, J. P., Fernandes, P. O. 2015).

Jitter is a periodic disturbance; shimmer is the magnitude disturbance. Both can be measured using four different formulas (Teixeira J. P. and Gonçalves, 2016), but in this work only the absolute and relative versions of each parameter will be worked on. Absolute jitter is the average absolute difference among successive periods whereas relative jitter is the absolute jitter divided by the average period, expressed in percentage (Teixeira J. P., Fernandes J., Teixeira F., Fernandes P. O., 2018).

Absolute shimmer, according to Teixeira J. P. *et al* (2018) is the logarithm of base 10 of the absolute mean of the magnitude ratio between consecutive periods multiplied by 20, given in decibel, whilst relative shimmer is the average absolute difference between amplitudes of successive periods, divided by the mean magnitude, expressed in percentage.

Table 1: Subset of subject of the Saarbruecken Voice Database used.

Test Groups	Number of Voice Samples			Average Participants' Age
	Female	Male	Total	
Control	123	71	194	36,74
Hyper-Functional Dysphonia	95	32	127	40,91
Vocal Fold Paralysis	100	65	165	57,52
Total	318	138	486	45,06

Autocorrelation is the correlation of a signal with itself, being a method of detecting the periodicity of the signal. According to Fernandes J. *et al.* (2019), this parameter provides a measure of the similar speech parts repeated along the signal.

The harmonic-to-noise ratio (HNR) gives the relation between the periodic and aperiodic components of a speech segment, whereas the noise-to-harmonic ratio (NHR) is given by the relation between the aperiodic component and the periodic component (Fernandes J., Teixeira F., Guedes, Junior, and Teixeira J. P., 2018).

2.3 Kohonen's Self Organizing Maps

Kohonen's Self-Organizing Maps (SOM) are structured through unsupervised competitive training, which allows the detection of similarities between the input data, grouping them (Haykin, 1999), (Kohonen, 1994). SOM are useful comparing to other neural networks because they are able to represent a multidimensional data set in a two-dimensional space (Haykin, 1999), (Kohonen, 1994), (Affonso, 2011).

The competitive learning process used by SOM works with the principle of competition between neurons, in which the winner has its weights modified to suit the next input vector. The definition of the winning neuron is given by the proximity between the input vector and the weight vector of the neuron (Haykin, 1999), (Affonso, 2011). This proximity is conceived by the Euclidian distance, expressed by equation (1). Where x is the input vector and w_j is the weights vector.

$$i(x) = \arg min\|x - w_j\| \quad j = 1,2, \dots n \tag{1}$$

When defined a winner, having already arranged the neurons in the topological map, one must define a neighborhood criterion between the neurons so that when a neuron wins, there is an adjustment of both the winner and the neighborhood (Kohonen, 1994), (Affonso, 2011). The Gaussian function is applied in the neighborhood, so that the more distant neighbors have a smaller adjusted value compared to the winner (Kohonen, 1994). Thus, equation (2) is applied to the winner and equation (3) is used in the neighborhood. The Gaussian operator is $\alpha^{(neighbor)}$, given by the expression (4). The σ symbol in equation (4) is the standard deviation of the dataset.

$$\boldsymbol{w}_{current}^{(winner)} = \boldsymbol{w}_{previous}^{(winner)} + \eta \times \left(\boldsymbol{x}^k + \boldsymbol{w}_{previous}^{(winner)}\right) \tag{2}$$

$$\boldsymbol{w}_{current}^{(neighbor)} = \boldsymbol{w}_{previous}^{(neighbor)} + \eta \times \alpha^{(neighbor)} \left(\boldsymbol{x}^k + \boldsymbol{w}_{previous}^{(neighbor)}\right) \tag{3}$$

$$\alpha^{(neighbor)} = e^{-\frac{\left\|\boldsymbol{w}_{previous}^{(winner)} - \boldsymbol{w}_{previous}^{(neighbor)}\right\|^2}{2\sigma^2}} \tag{4}$$

2.4 Hierarchical Clustering

The Hierarchical Clustering method is divided into: agglomerative, in which each object is a cluster and each iteration the union with other similar objects occurs until forming a single group; and divisive, which starts in a single large group containing all samples and recursively divides into smaller sets (Pavel, 2006).

This clustering method works with the (dis)similarity of the database elements, which is done through a linkage metric (Pavel, 2006). To find the (dis)similarity between each pair of objects in the database, the distance between these observations is calculated, given by the Euclidean distance, already expressed in Equation (1) (Gan, Ma, and Wu, 2007). After this calculation, it is possible to determine how the objects in the dataset should be grouped into clusters using the linkage metric (Gan Ma, and Wu, 2007), (Jain, Murty and Flynn, 1999). This metric characterizes the proximity of a pair of clusters, which defines whether the observations should merge or split, creating the hierarchy tree. This linkage can be complete, single, average, centroid, median, ward or weighted. The first uses the longest distance between objects in the two clusters, the average uses the mean distance between pairs of observations in two distinct groups, the centroid linkage, uses the Euclidean distance between the centers of two clusters, the median uses the Euclidean distance between the weighted centroids of the two groups.

Ward's linkage makes the incremental sum within the cluster as a result of joining two clusters and, finally, the weighted measure uses a recursive definition for the distance between two clusters (MathWorks, n.d.).

2.5 Pre-processing Data

The Neural Network toolbox of MATLAB® software was used to implement the artificial neural network algorithms. The raw data was pre-processed for cluster analysis. A normalization ranging from 0 to 1 was applied for the parameters, in which the maximum and minimum values of each parameter are identified. For each parameter, the normalization consists in the difference of each sample and its minimum divided by the difference of the maximum and minimum values. Equation (5) shows the normalization, wherein X is the parameter to be normalized and *i* the sample for each subject.

$$X_i = \frac{X_i - X_{i\,min}}{X_{i\,max} - X_{i\,min}} \quad i = 1,2, \ldots ,486 \tag{5}$$

After normalization, the neural network conditions must be adjusted. In this work, the characteristics of SOM were selected empirically based on data available in the literature, reaching a dimension of 100 neurons, with an initial neighborhood radius ranging from 1 to 10, in a hexagonal topology that is iterated 18000 times.

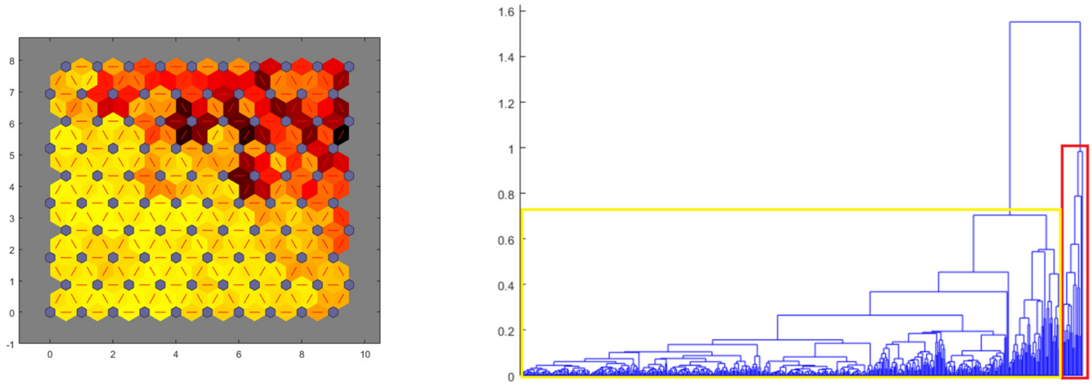
3 RESULTS AND DISCUSSION

Due to the sophisticated visualization of neurons in SOM, it is possible to notice that there is a division into two clusters. In Figure (1-a), the lower left corner points out the yellow to light orange color, which designates a proximity of the neurons forming a cluster. The dark orange tending to the red in upper right corner shows that the neurons are not so close to the ones of the lower left, forming a second group.

For a more assertive result of the clusters, the Hierarchical Clustering was also used. Like SOM, this network uses the Euclidean equation in order to determine the distance between each object in the database. In sequence, the linkage metric is used to create the clusters. To check if the linkage metric was chosen correctly, just compare the cophenetic distance. For a consistent result, this correlation must present a value close to 1, proving that the solution of this cluster represents the original data (MathWorks, n.d.). In terms of proximity between clusters, the average linkage is used, as it presents a better similarity in relation to other connection metrics, presenting a cophenetic correlation of 0.9297. Figure (1-b) shows the dendrogram producing two final clusters, which corroborates with the result presented by the Kohonen network. When the subjects of each group in the Hierarchical Clustering were analyzed, it was found that the groups were divided into a large group and a smaller one. All elements of the Control group belong to the largest set. Hyper-functional Dysphonia data also belong to this large set, with the exception of 2 elements. The other data of the small group are from the Vocal Fold Paralysis.

According to comparison of pathologies based on same parameters presented in Oliveira, Dajer, Fernandes, and Teixeira (2020) for the 3 groups under study, using descriptive statistical analysis, it was found that the Hyper-functional Dysphonia can be grouped with Control group and with Vocal Fold Paralysis group, but Vocal Fold Paralysis cannot be grouped with Control group. Since Hyper-functional Dysphonia, according to the descriptive statistical analysis, can be grouped with the two other groups, these subjects may become between the two (yellow and red) 'corners' of the SOM. This can be explained by the fact that the Hyper-functional Dysphonia in its primary phase does not present irregular traces in the laryngeal exam and the vocal symptoms are inconstant, having fatigue and episodes of vocal weakness as the main signs (Fawcus, 1991).

The (no) connection between the Vocal Fold Paralysis and the other two groups, may be probably, the reason for the distinction between their elements. The reason is because the Vocal Fold Paralysis and Hyper-functional Dysphonia pathologies are distinguished both in etiology and physiology. The Vocal Fold Paralysis is an injury to the recurrent laryngeal nerve, incapacitating the muscular contraction of the vocal folds (Chen, Jen, Wang, Lee, and Lin, 2007), (Toutounchi, Eydi, Golzari, Ghaffari, and Parvizian, 2014). Whereas the Hyper-functional Dysphonia causes increased tension in the laryngeal muscle, resulting in excessive stiffness of the vocal cords, bringing them closer together (Holmberg, Doyle, Perkell, Hammarberg, and Hillman, 2003), (Kandoğan, Koç, and Aksoy, 2009). In the comparison between the Control group and the Paralysis group there might be a difference, as the pathology inhibits the muscular contraction of the vocal folds. Therefore, the voice is altered, even in a minimal way.



(a) (b)

Figure 1: (a) Distance between the neighborhood of neurons in the Kohonen's Self-Organizing Maps; (b) Agglomerative hierarchy tree resulting from the input vector.

4 CONCLUSIONS

The paper presents clustering analysis using unsupervised ANNs, namely Kohonen's Self-Organizing Maps, and Hierarchical Clustering to gathering subjects of the Control group, Hyper-functional Dysphonia, and Vocal Fold Paralysis, using a set of speech parameters like jitter, shimmer, HNR, NHR and autocorrelation.

The clustering techniques analyzed here in order to group pathologies based on the acoustic parameters were successful, evidencing the results presented in previous research (Oliveira, Dajer, Fernandes, and Teixeira, 2020), in which there was no statistical distinction between Hyper-functional Dysphonia and the Control group, but there is a significant statistical difference between Vocal Fold Paralysis and Control group. Hence, the SOM presented the expected results considering that divided the dataset into two ‘corners’ with gradual scale between light yellow and dark red, likewise the descriptive statistical analysis method. This organization of subjects between the two ‘corners’ can be interpreted as the Control (Healthy) subjects in the light yellow, the Vocal Fold Paralysis in the dark red and Hyper-functional Dysphonia subjects between these two ‘corners’.

Even though it presented a good result, this work is still in progress. Therefore, this comparison will be extended to subjects with other pathologies in near future, adding more audios for each subject in order to obtain consistent results.

For future work, it is suggested to implement SOM and Hierarchical Clustering to the remaining pathologies and use other parameters extracted from the voice signal, such as the mel-frequency cepstral coefficient (MFCC), perceptual linear prediction (PLP), linear prediction cepstral coefficient (LPCC), among others.

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