Nonlinear Signal Processing for Vocal Folds Damage Detection Based on Heterogeneous Sensor Network

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Abstract

Heterogeneous sensor network-based medical decision making could facilitate the patient diagnosis process. In this paper, we present an intelligent approach for vocal folds damage detection based on patient's vowel voices using heterogeneous sensor network. Based on human voice samples and Hidden Markov Model, we show that transformed voice samples (linearly combined samples) follow Gaussian distribution, further we demonstrate that a type-2 fuzzy membership function (MF), i.e., a Gaussian MF with uncertain mean, is most appropriate to model the transformed voices samples, which motivates us to use a nonlinear signal processing technique, interval type-2 fuzzy

logic systems, to handle this problem. We also apply Short-Time-Fourier-Transform (STFT) and Singular-Value-Decomposition (SVD) to the vowel voice samples, and observe that the power decay rate could be used as an identifier in vocal folds damage detection. Two fuzzy classifiers, a Bayesian classifier, and a linear classifier are designed for vocal folds damage detection based on human vowel voices /a:/ and /i:/ only, and the fuzzy classifiers are compared against the Bayesian classifier and linear classifier. Simulation results show that an interval type-2 fuzzy classifier performs the best of the four classifiers.

Index Terms : Heterogeneous sensor network, interval type-2 fuzzy logic systems, Bayesian classifier, vocal folds, Short-Time-Fourier-Transform, singular-value decomposition.

1 Introduction

The proliferation of Heterogeneous Sensor Networks (HSN) has created a large amount of multi-sensor signals across multi-modality (e.g., optical, EO/IR, acoustic/seismic, RF, electromagnetic, mechanical, thermal, electrical, etc). Humans display a remarkable capability to perform multimodal signal processing despite noisy sensory signals and conflicting inputs. Humans are adept at network visualization, and at understanding subtle implications among the network connections. To date, however, human's innate ability to process and integrate signals from disparate, network-based sources has not translated well to signal processing in HSN. One of the great mysteries of the brain is cognitive control. How can the interactions between millions of neurons result in behavior that is coordinated and appears willful and voluntary? There is consensus that it depends on the prefrontal cortex (PFC) [1][2][3]. Many PFC areas receive converging inputs from at least two sensory modalities [4][5]. For example, the dorsolateral (DL) and ventrolateral PFC both receive projections from visual, auditory,

and somatosensory cortex. Furthermore, the PFC is connected with other cortical regions that are themselves sites of multimodal convergence. The Stroop task, naming the color of a conflict stimulus (e.g., the word GREEN displayed in red) [6][8], and Wisconsin card sort task (WCST) [9] are variously described as tapping the cognitive functions of either selective attention, behavioral inhibition, top-down control, working memory, or rule-based or goal-directed behavior [1]. In this paper, we are interested in rule-based approach for decision making based on HSN. In [7], opportunistic sensing for HSN was studied for two different cases, with independent modalities and correlated modalities. It showed that HSN with independent modality sensors, we can make analysis and information fusion for each single modality sensor network. On decision making based on sensor networks, many interesting works have been reported, for example, target recognition [10][11][12], sense-through-wall human detection [13], threat assessment [15], resource allocation [16], localization [17], etc. In this paper, we are interested in an important medical decision making problem, vocal folds damage detection, based on heterogeneous sensor networks with optical and acoustic modalities.

In decision theory, *ambiguity* about probabilities should not affect choices. However, recent experiments [14] showed that many people are more willing to bet on risky outcomes (e.g., gambling on a roulette wheel) than on an ambiguous one (e.g., chance of a terrorist attack based on meager or conflicting evidence), holding the judged probability of outcomes constant. So, the confidence in judged probability can vary widely for “risky” and “ambiguous”. Using functional brain imaging, Hsu et al [14] showed that the *level of ambiguity* in choices correlates positively with activation in the amygdala and orbitofrontal cortex, and negatively with a striatal system. This suggests that *degree of uncertainty* should be considered in decision making, contrary to traditional decision theory. So we introduce degree of uncertainty into vocal folds damage detection. The degree of uncertainty will be represented

using type-2 fuzzy logic.

The presence of any form of damage to the delicate vocal fold cover tissue will impair phonation, be it a polyp, nodule, edema or scarring. Polyps of the vocal folds are a separate entity occurring nowhere else in the larynx or in the human body [18]. The pathological diagnosis of the vocal folds is a field which demands more investigation. Traditionally, the methods of diagnosis are indirect laryngoscope, video-laryngoscope, and stroboscope light [19]. However, most of these methods need special instrument, and mainly depend on the experience of the pathologists. In [20], measurement of vocal fold intraglottal pressure and impact stress were studied, and the experimental results match well with analytical predictions and support a current theory of mechanical trauma leading to vocal nodules. In [21], a nonlinear model was proposed to study chaotic vibrations of vocal folds with a unilateral vocal polyp.

Many engineering approaches for voice pathology detection have been reported. In [22], direct speech feature estimation using an iterative Expectation-Maximization (EM) algorithm was applied to vocal fold pathology detection. In [19], a measure of pitch perturbation was shown to be most useful in pathological discrimination. A robust, rapid and accurate system for automatic detection of normal and pathological speech was studied in [23], which employed non-invasive, non-expensive and fully automated measures of vocal tract characteristics and excitation information. In [24], jitter estimation over short time intervals (short-term jitter) was used for voice pathology detection in the case of running or continuous speech, where short-term jitter estimations were provided by the spectral jitter estimator, which was based on a mathematical description of the jitter phenomenon. In [25], a system for remotely detecting vocal fold pathologies using telephone-quality speech was presented, which used a linear classifier, processing measurements of pitch perturbation, amplitude perturbation and harmonic-to-noise ratio derived from digitized speech recordings.

In [26], a neural network-based detector processing Mel frequency cepstral coefficients and their derivatives for normal/abnormal discrimination was presented. In [44], some preliminary results on vocal folds damage detection were presented based on patient voices. In [45], throat polyp detection based on compressed big data of voice with support vector machine algorithm was presented, and in [46] an intelligent throat polyp detection approach with separable compressive sensing was proposed.

In this paper, we are interested in detecting vocal folds damage using acoustic sensors based on the patient vowel voices only. Traditional pattern recognition techniques such as Bayesian classifier, known as the optimal classifier, could be used if the voice samples follow certain distribution, and this belongs to model-based statistical processing. As noted in [27], a shortcoming to model-based statistical signal processing is “... the assumed probability model, for which model-based statistical signal processing results will be good if the data agrees with the model, but may not be so good if the data does not.” In human’s voices, the voice amplitude is highly bursty, and we believe that no statistical model can really demonstrate the uncertain nature of the voice. Fuzzy logic systems (FLS) are model free. Their membership functions are not based on statistical distributions. In this paper, we, therefore, apply fuzzy techniques to vocal folds damage patient diagnosis.

In Section 2, we model voice samples using interval type-2 Gaussian membership function. In Section 3, Short-Time Fourier Transform and Singular-Value Decomposition are used to identify patient voice. Two fuzzy classifiers are presented in Section 4. In Section 5, a Bayesian classifier is proposed. Performances of four classifiers (including an existing linear classifier approach) are evaluated in Section 6. Conclusions are presented in Section 7.

2 Modeling Voice Samples Using Hidden Markov Model and Gaussian Primary MF with Uncertain Mean

In [41], autoregressive Hidden Markov Model (HMM) was used to represent voice samples x_i , which means we could have

$$x_k = - \sum_{i=1}^p b_i x_{k-i} + n_k \quad (1)$$

where n_k is Gaussian noise, and b_i ($i = 1, 2, \dots, p$) are the autoregression coefficients where p is autoregressive order. So

$$x_k - \sum_{i=1}^p c_i x_{k-i} = n_k \quad (2)$$

where $c_i = -b_i$. Which means the difference between samples (or their linear combinations) follows Gaussian distribution.

The experiments were performed in the clinic of Department of Otolaryngology Head and Neck Surgery, Peking University First Hospital. In our experiment, the heterogeneous sensor network consists of acoustic and optical sensors. The optical sensors are indirect laryngoscope, which is used to visualize the patient's vocal folds by a means other than obtaining a direct line of sight. However, this approach is not very accurate because of the poor quality of optical information, and sometime the vocal folds damage is not visible because it's hidden. The acoustic sensors are embedded in laptop computers. A voice data collection software, Cool Edit Pro 2.0 was installed in a SONY laptop computer which was equipped with high quality microphone with single channel (acoustic sensor). Each patient kept a distance of 5 cm between mouth and microphone. Each patient was asked to pronounce /a:/ and /i:/ twice using conversational natural voice. The sampling rate was 192KHz, and the data resolution was 32 bits. 20 patients participated in the test, of which 10 were male, and 10 were female. The patients were in ages of 28 to 81, and 10 patients were

normal, and 10 patients had vocal folds damage. Since the acoustic and optical modalities are independent in this experiment, we focus on acoustic modality in this paper.

Based on the voice data we have collected, we observed that the vowel /a:/ samples (x_k) do not follow Gaussian distribution, as illustrated in Fig. 1a, but when we choose $p = 5$, $c_1 = c_2 = c_3 = c_4 = 0$, $c_5 = 1$, i.e.,

$$x_k - x_{k-5} = n_k^a \quad (3)$$

the new sequences follow Gaussian distribution, as illustrated in Fig. 1b. Similarly, we observed that the vowel /i:/ samples (x_k) do not follow Gaussian distribution, as illustrated in Fig. 2a, but if we choose $c_1 = 1$, $p = 1$, i.e.,

$$x_k - x_{k-1} = n_k^i \quad (4)$$

follows Gaussian distribution, as illustrated in Fig. 2.

We, therefore, tried to model the the new transformed voice sequences n_k^a and n_k^i , to see if a Gaussian MF can match its nature. For n_k^a and n_k^i from each subject (human) for 100,000 samples, we equally separate it into 10 segments, and computed the mean m_i and standard deviation (std) σ_i of the i th segment, $i = 1, 2, \dots, 10$. We also computed the mean m and std σ of the entire sequence (100,000 samples). To see which value $-m_i$ or σ_i varies more, we normalized the mean and std of each segment using m_i/m , and σ_i/σ , and we then computed the std of their normalized values, σ_m and σ_{std} . As we see from the last row of Tables 1, $\sigma_m \gg \sigma_{std}$. We conclude, therefore, that if the transformed voice samples of each segment (short range) of the voice samples are Gaussian distributed, then the transformed voice samples in an entire voice samples (long range) are more appropriately modeled as a Gaussian with uncertain mean. This justifies the use of the Gaussian MFs with uncertain mean to model the transformed voice samples.

3 Identifying Vocal Folds Damage Patient Voice Using Short-Time Fourier Transform and Singular-Value Decomposition

STFT uses a slide window to determine the sinusoidal frequency and phase content of a signal as it changes over time. This form of the Fourier transform, also known as time-dependent Fourier transform, has a great many applications in speech processing. We will show that STFT - based approach could be used as an identifier for vocal folds damage detection.

For the continuous-time signal, the function to be transformed is multiplied by a nonzero window sliding along the time axis, therefore a two-dimensional expression can be defined as:

$$F(m, w) = \int_{-\infty}^{\infty} x(t)w(t - m)e^{-j\omega t}dt \quad (5)$$

where $x(t)$ is the function to be transformed and $w(t)$ is the window function. $F(m, w)$ represents sinusoidal values at the center of the window $w(t)$ that starts at time position m . The discrete STFT can be expressed as

$$F(m, w) = \sum_{n=0}^{N-1} x(n)w(n - m)e^{-j\omega n} \quad (6)$$

We apply a rectangular window, with its length 2048 and step size 1024. In Fig. 3, we plot the spectrogram $|F(m, w)|$ of a vocal folds damage patient vowel voices versus that of a normal person. Observe that the spectrogram could be used as an identifier in vocal folds damage detection.

The STFT of the voices is a matrix, how to extract its information for vocal folds damage detection? We use singular-value decomposition (SVD). The SVD is an important factorization of a rectangular real or complex matrix, with many applications in signal processing and statistics. Applications which employ the SVD include computing the pseudoinverse,

least squares fitting of data, matrix approximation, and determining the rank, range and null space of a matrix. Given $P \in C^{N \times M}$ (assuming $N > M$), and $rank(P) = r \leq M$. Determine a numerical estimate r' of the rank of the data sets matrix P by calculating the singular value decomposition

$$P = U \begin{bmatrix} \Sigma & 0 \\ 0 & 0 \end{bmatrix} V^T, \quad (7)$$

where, U is an $N \times N$ matrix of orthonormalized eigenvectors of PP^T , V is an $M \times M$ matrix of orthonormalized eigenvectors of P^TP , and Σ is the diagonal matrix $\Sigma = diag(\sigma_1, \sigma_2, \dots, \sigma_r)$, where σ_i denotes the i^{th} singular value of P , and $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_r > 0$. Using SVD, the STFT of voices could be diagonalized, and the diagonal values in Σ could be used to represent the speaker voice power decay in the frequency domain. Power decay rate means the how fast signal powers are reduced from one frequency to another. Generally the σ_1 is much higher than σ_2 , and the decay from σ_1 to σ_2 somehow represent how a person could handle his voice freely. For illustration purpose, we plot the singular values (σ_i) ($i = 1, 2, \dots, 10$) in Fig. 4 for the two patients whose spectrogram were plotted in Fig. 3. Observe Fig. 3, the voice power decay rate, i.e., $Pd = \sigma_1 - \sigma_2$, is higher for a normal person than that of a patient with vocal folds damage, which means that a normal person could handle his/her voices more freely (with higher power changes from one frequency to another frequency). So voice power decay rate could be used as an identifier on vocal folds damage detection. In this paper, we will use the vowel /a:/ and /i:/ power decay rate in fuzzy classifiers for vocal folds damage detection.

4 Two Fuzzy Classifiers for Vocal Folds Damage Detection

In this Section, we use type-1 and interval type-2 FLSs for vocal folds damage detection.

4.1 Type-1 FLSs

A FLS is described by fuzzy IF-THEN rules which represent input-output relations of a system. For classification, in a type-1 FLS with a rule base of M rules, each having p antecedents, the l th rule, R^l , is expressed as:

$$R^l: \text{IF } x_1 \text{ is } F_1^l \text{ and } x_2 \text{ is } F_2^l \text{ and } \dots \text{ and } x_p \text{ is } F_p^l \text{ THEN } y^l = c^l$$

in which $l = 1, 2, \dots, M$, the consequent c^l are crisp values (e.g., +1 or -1 in this paper), and, F_k^l ($k = 1, 2, \dots, p$) are type-1 fuzzy sets. For a singleton FLS, the rule firing degree is

$$f^l = \mathcal{T}_{k=1}^p \mu_{F_k^l}(x_k) \quad (8)$$

where $\mathcal{T}$ denotes a t -norm (minimum or product).

In this paper, we use an unnormalized output [42] for the FLS, namely

$$y = \sum_{l=1}^M f^l y^l, \quad (9)$$

because we make a decision based on the sign of the output, and normalization operation will not change the sign. If the domain of interest had 3 or more choices, we would use a normalized output for decision making.

In Section 6, we use type-1 FLSs for vocal folds damage detection based on voice samples only.

4.2 Interval Type-2 FLSs

In a type-2 FLS with a rule base of M rules, in which each rule has p antecedents, the l th rule R^l , is expressed as:

$$R^l: \text{ IF } x_1 \text{ is } \tilde{F}_1^l, \text{ and } x_2 \text{ is } \tilde{F}_2^l, \text{ and, } \dots, \text{ and } x_p \text{ is } \tilde{F}_p^l \text{ THEN } y^l = c^l.$$

The firing degree, F^l , of rule R^l is

$$F^l = \sqcup_{\mathbf{x} \in \mathbf{X}} \{ [\mu_{\tilde{X}_1}(x_1) \sqcap \mu_{\tilde{F}_1^l}(x_1)] \sqcap \dots \sqcap [\mu_{\tilde{X}_p}(x_p) \sqcap \mu_{\tilde{F}_p^l}(x_p)] \} \quad (10)$$

where $\mathbf{X} = X_1 \times X_2 \times \dots \times X_p$ is the measurement domain of $\mathbf{x} = [x_1, x_2, \dots, x_p]$, and $\sqcup$ and $\sqcap$ are join and meet operations [28]. General type-2 FLSs are computationally intensive because it is not easy to evaluate F^l in (10). Things simplify a lot when secondary membership functions are interval sets, in which case secondary memberships are either 0 or 1, such simplifications make the use of a type-2 FLS practical.

In [28], Liang and Mendel proposed the theory and design of interval type-2 fuzzy logic systems. They proposed an efficient and simplified method to compute the input and antecedent operations for interval type-2 FLSs, one that is based on a general inference formula for them. They introduced the concept of upper and lower membership functions (MFs) and illustrate their efficient inference method for the case of Gaussian primary MFs. They also proposed a method for designing an interval type-2 FLS in which they tuned its parameters [29]. They applied interval type-2 FLS to a number of very important applications where uncertainties abound, such as fading channel equalization [32] and co-channel interference elimination [33], network video traffic modeling and classification [34], connection admission control for ATM network [35]. Recently, interval type-2 FLSs were applied to sensor network lifetime estimation [36], and cross-layer optimization in ad hoc networks [37][38], event detection [39][40], etc.

In Section 6, we use type-1 and interval type-2 FLSs as fuzzy classifiers for vocal folds damage detection. Our fuzzy classifiers are model-free. To compare them against a model-based classifier, we develop a Bayesian classifier in Section 5.

5 Bayesian Classifier for Vocal Folds Damage Detection

Bayesian decision theory [43] provides the optimal solution to the general decision-making problem. We assume that each patient has equal probability to have vocal folds damage, i.e., H_1 : *Damaged*, and H_2 : *Normal*, so $p(H_1) = p(H_2) = 0.5$. If each transformed vowel voice samples (/a:/ and /i:/) of patient j follows Gaussian distribution, $\mathbf{x}_j \triangleq [x_j^a x_j^i]^T$ stands for the samples from patient j for vowel /a:/ and /i:/, then

$$p(\mathbf{x}_j|v_j) = \frac{1}{(2\pi)^{|\Sigma_j|^{1/2}}} \exp\left[-\frac{1}{2}(\mathbf{x}_j - \mathbf{m}_j)^T \Sigma_j^{-1}(\mathbf{x}_j - \mathbf{m}_j)\right] \quad (11)$$

where $\mathbf{m}_j \triangleq [m_j^a, m_j^i]^T$ and $\Sigma_j = \text{diag}\{\sigma_j^{a2}, \sigma_j^{i2}\}$ are the mean vector (2×1) and covariance matrix (2×2) of $\mathbf{x}_j$. In this case,

$$p(\mathbf{x}|H_1) = \sum_{i=1}^{10} p(\mathbf{x}|v_i)p(v_i) \quad (12)$$

$$p(\mathbf{x}|H_2) = \sum_{i=11}^{20} p(\mathbf{x}|v_i)p(v_i) \quad (13)$$

Based on Bayes decision theory, since $p(H_1) = p(H_2) = 0.5$, we obtain the decision rule:

$$\text{Claim vocal folds damage if } p(\mathbf{x}|H_1) > p(\mathbf{x}|H_2) \quad (14)$$

$$\text{No vocal folds damage if } p(\mathbf{x}|H_1) < p(\mathbf{x}|H_2) \quad (15)$$

$$\text{Not sure if } p(\mathbf{x}|H_1) = p(\mathbf{x}|H_2) \quad (16)$$

This Bayesian vocal folds damage detector will be used in Section 6.

6 Simulations

We extract the general features and behavior of /a:/ and /i:/ voices for 20 patients, of which 10 have vocal folds damage and 10 have no vocal folds damage, and determine one discriminant rule for each patient in the domain of interest. In choosing the antecedents of the fuzzy classifier, we make full use of the statistical knowledge (mean and std) obtained from the patient voices. We used 100,000 samples in vowel /a:/ and /i:/ respectively to establish a discriminant rule for each patient. All-in-all, we obtained 20 rules, one per patient.

To evaluate the performance of the 2 fuzzy detectors, we used another group of 20 patients (testing group), which has no overlap with the first group of 20 patients whose vowel samples were used for fuzzy rules. By this means, it would help to demonstrate that our classifiers are robust. We also collected 100,000 voice samples for /a:/ and /i:/ respectively for each patient in the testing group. To demonstrate that our classifiers are able to detect vocal folds damage using a small number of samples, we made our detection based on every 5,000 samples, with 20 independent detections ($20 \times 5,000$) for each patient. During testing, we obtain the mean $\mathbf{m}^t = [m_a^t, m_i^t]$ for each 5,000 /a:/ and /i:/ samples.

6.1 Design of Four Vocal Folds Damage Detectors

6.1.1 Design of Type-1 Fuzzy Vocal Folds Damage Detector

For a type-1 fuzzy classifier, the l th rule, R^l , is ($l = 1, \dots, 10$):

R^l : IF the transformed /a:/ voice is F_1^l and the transformed /i:/ voice is F_2^l and /a:/ power decay rate is F_3^l and /i:/ power decay rate is F_4^l THEN this patient has vocal folds damage (+1) [or normal (-1)].

The antecedents F_k^l ($k = 1, 2, 3, 4$) are described by a type-1 Gaussian MF whose mean, m_p^l , and std, σ_p^l , are determined by known patient voice samples. More specifically, m_1^l and σ_1^l

are the mean and std of voice /a:/ samples in the 100,000 samples of patient l in the first group; m_2^l and σ_2^l are the mean and std of /i:/ samples in the 100,000 samples of patient l in the first group. To determine m_3^l , σ_3^l , m_4^l , and σ_4^l , we partition the voice samples into 10 segments for /a:/ and /i:/ respectively, and obtain the STFT of each segment. Then apply SVD to the STFT matrix to obtain the power decay rate for each segments. The mean and std of the 10 power decay rates are m_3^l (m_4^l) and σ_3^l (σ_4^l). The consequent $y^l = c^l$ in Section 4.1 corresponds to $y^l = +1$ (vocal folds damage) or $y^l = -1$ (normal) in the fuzzy detector. The +1 or -1 for y^l is truly a representation of linguistic using numerical value. Since it's a binary decision, so we use +1 or -1.

For a *type-1 fuzzy detector*, its input, $\mathbf{m}^t = [m_a^t, m_i^t, Pd_a, Pd_i]$, is obtained from 5,000 vowel samples from patient in the testing group. Pd_a and Pd_i are the power decay rate for /a:/ and /i:/.

6.1.2 Design of Type-2 Fuzzy Vocal Folds Damage Detector

For type-2 fuzzy classifiers, the l th rule, R^l , is ($l = 1, \dots, 10$):

R^l : IF the transformed /a:/ voice is $\tilde{F}_1^l$ and the transformed /i:/ voice is $\tilde{F}_2^l$ and /a:/ power decay rate is F_3^l and /i:/ power decay rate is F_4^l THEN this patient has vocal folds damage (+1) [or normal (-1)].

The antecedents $\tilde{F}_k^l$ ($k = 1, 2, 3$) are described by a type-2 MF, i.e., a Gaussian MF with uncertain mean, whose mean $m_k^l \in [m_{k1}^l, m_{k2}^l]$ and std σ_k^l are determined by the voice samples of patients in the first group. F_3^l and F_4^l are same as those in type-1 fuzzy detector.

More specifically, σ_k^l ($k = 1, 2$) are determined using the same method as described in Section 6.1.1, and m_{k1}^l and m_{k2}^l are determined as follows. We divided the 100,000 frames of the l th known patient into 10 equal-length (10,000 samples) segments, and computed the

mean m_1^{lj} of /a:/ samples in the j th segment ($j = 1, \dots, 5$). Let

$$m_{11}^l = \min_{j=1, \dots, 10} m_1^{lj} \quad (17)$$

$$m_{12}^l = \max_{j=1, \dots, 10} m_1^{lj} \quad (18)$$

so $[m_{11}^l, m_{12}^l]$ is the range of uncertain mean of /a:/ voice samples of the l th known patient.

We obtained the ranges of uncertain mean of /i:/ samples ($[m_{21}^l, m_{22}^l]$) in a similar manner.

For a *type-2 fuzzy detector*, its input, $\mathbf{m}^t = [m_a^t, m_i^t, Pd_a, Pd_i]$, is obtained from 5,000 vowel samples from patient in the testing group.

6.1.3 Design of Bayesian Classifier

Observe from (11), that the Bayesian classifier needs $\mathbf{m}_i = [m_i^a, m_i^i]^T$ and $\Sigma_i = \text{diag}\{\sigma_i^{a2}, \sigma_i^{i2}\}$.

In our design, m_i^a and σ_i^a are the mean and std of vowel /a:/ in the 100,000 samples of patient i in the first group; similarly, m_i^i and σ_i^i are the mean and std of vowel /i:/ in the 100,000 samples of patient i in the first group; and, its input $\mathbf{x} \triangleq \mathbf{m}^t$, where $\mathbf{m}^t$ is obtained from the mean value of 5,000 voice samples from a patient in the testing group.

6.1.4 Design of Linear Classifier

We compared our approaches with an existing approach, linear classifier proposed in [25], which processing measurements of pitch perturbation, amplitude perturbation, and homonic-to-noise ratio derived from digitized speech recording. The linear classifier can be summarized as follows. Let $\mathbf{x}$ be a column vector containing d feature values which is assigned to one of two classes, i.e., normal or damaged. Based on the training sets, we could obtain the mean vectors $\mathbf{m}_1$, $\mathbf{m}_2$, and covariance matrix Σ (for both classes) of the $\mathbf{x}$. Assume the prior probability of both classes are equal, the discriminant value y is

$$y = (\mathbf{m}_1 - \mathbf{m}_2)^T \Sigma^{-1} \mathbf{x} - \frac{1}{2} (\mathbf{m}_1 - \mathbf{m}_2)^T \Sigma^{-1} (\mathbf{m}_1 - \mathbf{m}_2) \quad (19)$$

and then the posterior probabilities for class 1 (normal) and class 2 (damaged) are then calculated using

$$P(1|\mathbf{x}) = \frac{\exp(y)}{\exp(y) + 1} \quad (20)$$

$$P(2|\mathbf{x}) = 1 - P(1|\mathbf{x}) \quad (21)$$

The final classification decision is obtained by choosing the class with the highest posterior probability.

In the pitch perturbation features, we used mean value of F_0 , maximum F_0 , minimum F_0 , std of F_0 , phonatory frequency range, mean absolute jitter, jitter, pitch perturbation quotient (smoothed over 5 pitch periods). In the amplitude perturbation features [25], we used mean, maximum, minimum, std, mean absolute shimmer, shimmer percentage, shimmer decibels, amplitude perturbation quotient smoothed over 5 pitch period. In Harmonic-to-Noise ratio is calculated based on the procedure given in [25]. The decision is made based on human vowel voices /a:/ or /i:/ only.

6.2 Performance Analysis

We computed the average probability of miss detection ($p_r(\epsilon)$) for each fuzzy detector as well as for the Bayesian detector in $20 \times 20 = 400$ independent classifications (20 patients each with 20 5,000-sample segments), and please be aware that the voices of the first group patients were used to design the fuzzy rules, and the testing group of patients have no overlap with the first group. Simulations show that $p_r(\epsilon) = 25\%$ for Bayesian classifier, $p_r(\epsilon) = 18\%$ for type-1 fuzzy classifier, and $p_r(\epsilon) = 14\%$ for type-2 fuzzy classifier. We evaluated the linear classifier in [25], and simulations show that $p_r(\epsilon) = 21\%$.

Bayesian classifier is known as the optimal classifier [43], but why it can't achieve the best performance? There are several possible reasons.

1. Fuzzy classifiers use more identifiers, i.e., transformed voice samples as well as voice power decay rate from STFT and SVD, whereas Bayesian classifier only uses transformed voice samples.
2. The voice power decay rate from STFT and SVD doesn't follow any statistical distribution, so this knowledge couldn't be incorporated into Bayesian classifier.
3. The transformed voice samples do not exactly follow Gaussian distribution, but a Gaussian with uncertain means. Bayesian classifier is a model-based approach, so it can't achieve the best performance when the model doesn't match real-world data.

The linear classifier could not perform well because the training group data and the testing group data have no overlap, so the mean vector and variance matrix obtained from the training data couldn't fully reflect the pitch, amplitude, and harmonic-to-noise ratio in the testing data.

Although type-2 fuzzy classifier performs the best, it has highest complexity among the four classifiers. In Table 2, we summarize the classification performance and computational complexity of the four classifiers.

7 Conclusions

We have presented a new approach for vocal folds damage detection based on patient's vowel voices using interval type-2 fuzzy logic system. Based on human voice samples and Hidden Markov Model, we showed that transformed voice samples (linearly combined samples) follow Gaussian distribution, further we demonstrated that a type-2 fuzzy MF, i.e., a Gaussian MF with uncertain mean, is most appropriate to model the transformed voices samples. We also applied STFT and SVD to the vowel voice samples, and observe that the voice power decay

rate could be used as an identifier in vocal folds damage detection. Two fuzzy classifiers and a Bayesian classifier were designed for vocal folds damage detection based on human vowel voices /a:/ and /i:/ only, and the fuzzy classifiers are compared against the Bayesian classifier and a linear classifier. Simulation results showed that an interval type-2 fuzzy classifier performs the best of the four classifiers.

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Table 1: An example: mean and std values for 10 segments (10,000 samples/segment) and the entire voice (100,000 samples) from one person, and their normalized std.

Voice Data	Vowel /a:/		Vowel /i:/	
	mean	std	mean	std
Segment 1	-9.6012	9.8983×10^4	616.1160	3.9892×10^4
Segment 2	2.2539	9.7968×10^4	-551.6035	4.9503×10^4
Segment 3	-6.4511	9.8753×10^4	-26.1122	4.7019×10^4
Segment 4	-0.8452	9.7641×10^4	-204.7233	4.5823×10^4
Segment 5	14.5417	9.6117×10^4	801.8690	4.2358×10^4
Segment 6	-14.2853	9.5306×10^4	-762.8290	4.1863×10^4
Segment 7	0.9474	9.7104×10^4	-20.7100	4.5593×10^4
Segment 8	7.6797	9.7449×10^4	-37.0950	4.6036×10^4
Segment 9	10.6494	9.7594×10^4	522.1380	4.6445×10^4
Segment 10	-15.1029	9.7751×10^4	-50.2020	4.2348×10^4
Entire Voice	-1.0214	9.7468×10^4	29.8584	4.4774×10^4
Normalized std	10.0384	0.0113	16.6340	0.0655

Table 2: The classification performance and number of parameters in 4 different classifiers.

Classifier	$p_r(\epsilon)$	Total Number of Parameters
<i>Type-1 Fuzzy Classifier</i>	18%	80
<i>Type-2 Fuzzy Classifier</i>	14%	120
<i>Bayesian Classifier</i>	25%	80
<i>Linear Classifier</i>	21%	45

(a)

(b)

Figure 1: (a) The histogram of 100,000 voice /a:/ samples x_k ; (b) the histogram of transformed voice samples $x_k - x_{k-5}$ and its matching to a Gaussian distribution.

(a)

(b)

Figure 2: (a) The histogram of 100,000 voice /i:/ samples x_k ; (b) the histogram of transformed voice samples $x_k - x_{k-1}$ and its matching to a Gaussian distribution.

Figure 3: Spectrogram using a Short-Time Fourier Transform (STFT). Window size of STFT is 2048, and overlap between two neighbor window is 1024. (a) is from a vocal folds damage patient speaking vowel /a:/; (b) is from a normal person speaking vowel /a:/; (c) is from the vocal folds damage patient speaking vowel /i:/; (d) is from the normal person speaking vowel /i:/.

Figure 4: The 10 largest singular values of STFT of two patients in Fig. 3.