Analysis of Tidal Breathing Flow Volume Loops for Automated Lung-Function Diagnosis in Infants

Steffen Leonhardt*, Senior Member, IEEE, Peter Ahrens, and Vojislav Kecman

Abstract—Lung-function analysis in the age group below 5 years has not yet found its way into clinical routine. One possible candidate for routine lung testing in this age group is the analysis of tidal breathing flow-volume (TBFV) loops, a technique that has not yet proven to be capable of detecting obstructive and other lung disorders at an early stage. We present a new set of mathematical features useful to analyze TBFV loops. These new features attempt to describe more complex properties of the loops, thus imitating medical judgment of the curves (e.g., “round,” “triangular,” etc.) in a “linguistic” manner. Furthermore, we introduce support vector machines (SVMs) as a method for automated classification of diseases. In a retrospective clinical trial on 195 spontaneously breathing infants aged 3 to 24 months, the discriminant power of individual features and the overall diagnostic performance of SVMs is investigated and compared with the results obtained with traditional Bayes’ classifiers. We demonstrate that the proposed new features perform better in all examined disease groups and that depending on the disease, the classification error can be reduced by up to 50%. We conclude that TBFV loops may have a much stronger discriminant power than previously thought.

Index Terms—Infant lung-function diagnosis, tidal breathing flow-volume (TBFV) loops, support vector machines (SVM).

I. INTRODUCTION

The incidence of allergic lung diseases in early childhood continues to increase, with reported incidences of up to 10% [1]. To avoid development of a chronic disease status, early management of the disease, and therefore, methods for early detection are crucial, for this, an easy-to-use screening method for very young children would be advantageous.

In adolescence and adult life, there are established methods to assess lung function. By contrast, lung-function testing in infancy as a general concept is relatively new in clinical research and practice [2], and many clinicians still view these methods as experimental. Fortunately, there is growing support for its use [3], [4]. Several techniques adapted to the special needs of infants have been investigated over the past few decades, including body plethysmography [5], measurements of functional residual capacity (FRC, see [6]) using N₂ wash-out [7], and He wash-in [8], forced expiration techniques using compressible jackets [9], [10] and electric impedance tomography (EIT) to visualize regional ventilation [11], [12]. Another technique is the analysis of tidal breathing flow-volume (TBFV) loops [13]–[15]. Reports are also available on the comparison of methods, such as gas-based FRC methods and plethysmographic methods [16] or plethysmographic FRC measurements compared to forced expiratory flow measurements and tidal breathing analysis [17]. In addition, some of these technical methods have been used to conduct research on histamine [18] or metacholine challenge tests [19], and on the responsiveness of bronchodilators [20].

Of the methods mentioned earlier, especially the analysis of TBFV loops is a promising candidate for routine testing in an outpatient department and for screening, in general practice, mainly due to its simplicity. Basically, this method evaluates the shape of the air flow signal \( V_{\text{breath}}(t) \) and only requires a pneumotachograph attached to the mouth and nose of the patient via a face mask (see Fig. 1). The underlying measurement principle typically is the pressure drop across a laminar flow grid.

Tidal breathing itself does not yield very much information in the adult patient. However, due to the small geometric dimensions of the tracheal tree, an infant is much closer to its maximal work of breathing during tidal breathing and any additional load during disease may bring the infant to a state similar to a forced expiration maneuver [22]. Therefore, whereas it takes some time before pathologies show up in adult tidal breathing, tidal breathing in infants may be discriminant enough to diagnose various pathologies [23].
Integration over time of $V_{\text{breath}}(t)$ gives the corresponding tidal lung volume $V_T = \Delta V_{\text{lung}}$. Hints on proper use of the technique, like calibration, using face masks and avoiding drifts, are provided, e.g., [24]. Typically, specific volumes, flows or time periods are evaluated for diagnostic purposes. For historical reasons, it has become standard to evaluate the shape of the flow-volume (FV) diagram (phase diagram) rather than the shape of the flow curve in time domain. To obtain such a TBFV-loop, flow and corresponding volume are plotted against each other in “phase space.” Thus, for a healthy infant, who breathes rather sinusoidally, an ellipsoid shape can be expected in phase plane. However, as shown in Fig. 2, these loops significantly change shape with specific pathologies.

For example, obstructive diseases like asthma, bronchitis or induced by reflux (loops 3–5) seem to be characterized by a triangular shape during expiration, whereas inspiration looks normal. Note that clinicians tend to avoid the term “asthma” for patients below 4–5 years of age. Instead, the pathology is often called “recurrent wheeze.” A stenosis (tracheal narrowing) and some malacias (weaknesses of tracheal cartilago) may express inspiratory or expiratory flow limitations resulting in a rectangular shape (loops 7, 8, and 10). In more severe forms of malacias, the weak cartilage may collapse (“collapse phenomenon,” loop 9). Finally, high-frequency oscillations (loop 2) may be a sign of mucous. Note that other physiologic breathing actions of the infant (like grunting, braking, or the like) would also change the shape of the TBFV loop, but were either not present or excluded from this study.

In the literature, some authors have reported on shape analysis of FV loops. For example, Morris et al. introduced several FV-loop analysis with body plethysmography [25]. The derived curve indexes were tested on ca. 100 children and adult patients. A new curvature index was introduced to classify the shape of the expiratory limb in adult patients in [26]. As was shown, this index correlates well with the volume expired during forced expiration volume in 1 s (so-called FEV1). For asthmatic children, a second-order polynomial curve fitting and an average curvature index to capture the overall shape (convexity) of the expiratory limb was introduced in [27]. Finally, for infant TBFV loops, some qualitative results on shape analysis of TBFV loops were presented in [28].

A different type of shape analysis [like a concavity indexes and symptoms based on fast Fourier transform (FFT)] has been provided in [29], in this case, in combination with neural networks for automatic pattern recognition.

Over the years, the discriminant power of TBFV-loop analysis has often been discussed and repeatedly challenged (e.g., [30]). While there are reports on specific TBFV-loop features, like specific volume and time relationships, which may be used as a symptom for lung disease, the focus has often been on the investigation of only a single feature at one time [14], [31]–[33]. For some of the known TBFV-loop features, normal values and standard deviations for chronic lung disease (CLD, $n = 48$) and healthy controls ($n = 48$) have been presented in [28]. Also, they classify loop shapes by terms like “convex or concave expiratory limb” or “flow braking.” In a recent study [34] on a rather large number of patients ($n = 424$), especially the features time to peak tidal expiratory flow/time for expiration (TPTEF/TE) (see Table II next) and respiratory rate turned out to be the features with highest discriminant power for healthy status versus bronchopulmonary dysplasia (BPD). However, the significance of some of these classical features remained questionable, possibly because the analysis of isolated symptoms may not describe the complex loop patterns found in clinical practice with sufficient accuracy.

Thus, in this study, we first summarize the properties of the classical infant TBFV-loop features. Afterward, we present several improved features originally introduced in [21], which allow to capture more complex loop properties (like roundness, triangularity, etc.). Finally, we show that, for this specific application, the discriminant power may be increased by choosing more powerful pattern-recognition tools, i.e., support vector machines (SVMs) instead of Bayes’ classifiers.

II. METHODS

Generally, an automated diagnostic task includes two sequential steps, namely “feature extraction” and “diagnosis.” Feature extraction is typically a heuristic procedure and strongly depends on the nature of the task. It results in a data reduction and may be generally viewed as a continuous mapping from signal space to feature space. In general, signal space may be $k + 1$-dimensional ($k$ time-dependent signals). During a specific observation period, the signals are mapped on an $m$-dimensional feature vector $F$ (see Fig. 3).

Note that in our case, $k = 1$ [which means $x(t) = V_{\text{breath}}(t)$] and the observation time window is the time $T_i$ required for one breath stroke.

In the second step, the feature vector is mapped to the disease vector. In the specific application, this vector is labeled from 1 to $n$, where $n$ is the number of diseases, and here, $n = 10$. In a diagnostic support environment, both steps are equally
important. Features should be as significant as possible, and their choice is crucial. However, the pattern-recognition algorithm should be as powerful as possible, in order not to lose any information.

Next, we first present the hardware and the patient population included into this study. Then, we will introduce the classical methods to extract features from TBFV loops and introduce new loop features. Finally, we will explain the rationale of SVMs as a pattern-recognition tool suitable for automated diagnostic support.

### A. Measurement Scenario

All tidal breathing spirometric measurements were performed with a 2600 Pediatric Pulmonary Function Laboratory (SensorMedics Corporation, Yorba Linda, CA), see [35]. The infants were either sleeping or actively sedated using chloralhydrate (dosing range [50, 100] mg/kg body weight [36]).

Note that regularity of tidal ventilation may be influenced by sleep stage [37] and depth of sedation [38], [39]. Within this paper, we did not formally study such effects. To avoid irregularities, we visually checked all recorded TBFV loops for similarity in each data acquisition session.

### B. Patient Population

The mathematical techniques developed in this paper were tested on data obtained from a patient population of \( n = 195 \) subjects aged 3 to 24 months. From a large patient database, nine groups of pathologies and one healthy reference group were formed. Table I shows the distribution of the pathologies.

The healthy subjects underwent lung-function diagnosis for nonpulmonological reasons (e.g., as part of a neurological investigation). Even though this might be debatable, these patients were classified as “lung healthy,” if there was no evidence of any pulmonological disorder.

For all other patient groups, only infants with additional diagnoses, such as, e.g., by pH metry or by bronchoscopy [40], [41] serving as a gold standard were enrolled. Thus, only infants who, for reasons independent of this study, underwent lung-function diagnosis at the Department of Pediatrics of Johann Wolfgang Goethe University Hospital (Frankfurt, Germany), were included into this retrospective study. In case of a positive pH metry, if, in addition, the bronchoscopic findings supported an inflammation of the lower airways, the diagnosis was defined as “gastroesophageal reflux.” If an allergic anamnesis was present and in coincidence with the bronchoscopic findings, the diagnosis was defined as “asthma.”

All data was rendered anonymous prior to analysis. Informed consent to participate in the investigation was obtained from the parents of all patients prior to being enrolled.

### C. Feature Extraction Using Classical-Loop Features

In the past, the analysis of TBFV loops was performed by observing characteristic flow or volume measurements. Several characteristic loop features have been introduced in the past [13], [24], [28]. Because these loop parameters are not new, in this paper, we refer to these loop features as “classical” ones; some of these features are shown in Fig. 4.

To avoid dependence on size or bodyweight, most of these classical features are normalized by relating them to tidal volume or similar variables. In addition, several specific timing relationships are provided. Table II lists a selection of important relative loop features (see [35]).

However, as one can see in Table II, most of these classical-loop features only describe specific points of the loop, or at best, timing ratios, which was considered to limit their discriminant power (i.e., their ability to separate different diseases) by the authors. Therefore, we aimed to develop more complex, linguistic features (like “round” or “triangular-shaped”), thus imitating the way TBFV loops are currently diagnosed in some experimental clinical settings today.
TABLE II
NORMALIZED CLASSICAL FLOW, TIME, AND VOLUME FEATURES

<table>
<thead>
<tr>
<th>feature</th>
<th>meaning</th>
<th>physical unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>PTEF/VE</td>
<td>max. exp. flow related to VE</td>
<td>[l/s]</td>
</tr>
<tr>
<td>TEF50/VE</td>
<td>exp. flow at 50 % volume related to VE</td>
<td>[l/s]</td>
</tr>
<tr>
<td>TEF25/VE</td>
<td>exp. flow at 25 % volume related to VE</td>
<td>[l/s]</td>
</tr>
<tr>
<td>PTEF/VI</td>
<td>max. insp. flow related to VI</td>
<td>[l/s]</td>
</tr>
<tr>
<td>TIF50/VI</td>
<td>insp. flow at 50 % volume related to VI</td>
<td>[l/s]</td>
</tr>
<tr>
<td>TEF50/TIF50</td>
<td>exp. flow related to insp. flow, both at 50 % volume</td>
<td>[l]</td>
</tr>
<tr>
<td>TEF50/TEF10</td>
<td>exp. flow at 50 % volume related to exp. flow at 10 %</td>
<td>[l]</td>
</tr>
<tr>
<td>TEF25/PTEF</td>
<td>exp. flow at 25 % volume related to max. exp. flow</td>
<td>[l]</td>
</tr>
<tr>
<td>VPTEF/VE</td>
<td>volume fraction when reaching max. exp. flow</td>
<td>[l]</td>
</tr>
<tr>
<td>TE/TI</td>
<td>exp. time related to insp. time</td>
<td>[l]</td>
</tr>
<tr>
<td>TPTEF/TE</td>
<td>fraction of time to reach PTEF related to total expiration time</td>
<td>[l]</td>
</tr>
<tr>
<td>TPTIF/TI</td>
<td>fraction of time to reach PTIF related to total inspiration time</td>
<td>[l]</td>
</tr>
</tbody>
</table>

D. Feature Extraction Using New Loop Features

An important goal of this study was to generate linguistically complex, yet quantifiable TBFV-loop features that extract more information from the loop and can therefore better distinguish various pathologies from the healthy norm as compared to the classical TBFV-loop features. For all the new features presented next, all TBFV loops were normalized to $\pm 1$ and centered around the origin prior to any computation. This measure simplifies the computations and also guarantees the elimination of the influence of size and body weight.

Note that normalization was performed for the $y$-axis and the $x$-axis separately. The $y$-axis was normalized by setting the maximum flow during inspiration to $-1$ and during expiration to $+1$. For the $x$-axis, normalization was performed by setting $\Delta V_{\text{lung}} = 0$ to $-1$ and $\Delta V_{\text{lung, max}} = +1$. Thus, $r_{\text{circumscribed}}$ will always $>1$, while $r_{\text{inscribed}} < 1$. Only for a perfect semicircle, one would find $r_{\text{circumscribed}} = r_{\text{inscribed}} = 1$.

1) Sphericity: The roundness of a TBFV loop may be quantified by dividing the radius of the inscribed semicircle by the radius of the circumscribed semicircle. The symbol for roundness shall be $\circ$. For expiration, this leads to

$$\circ_{\text{exp}} = \frac{r_{\text{inscribed, exp}}}{r_{\text{circumscribed, exp}}}.$$  \hspace{1cm} \hspace{1cm} (1)

Both the inscribed and the circumscribed semicircle must also be centered around the origin. Note that even the presumably circular TBFV loop of an healthy individual is not completely circular after normalization. For expiration, it becomes clear that the sphericity is a rather discriminant feature.

2) Triangularity: One possible way to quantify triangularity is to relate the area of the inscribed triangle (connection between the normalized PTEF and the starting and end points of the loop) to the area under the TBFV loop. For expiration (and similarly for inspiration), this leads to

$$\nabla_{\text{exp}} = \frac{1}{0.5 \cdot \text{PTEF} \cdot V E} \int_{0}^{\Delta V_{\text{lung}} = 0} V_{\text{breath}} dV - 1.$$ \hspace{1cm} \hspace{1cm} (2)

Thus, $\nabla \approx 0$, if the shape is very triangular (with $\nabla > 0$ indicating a more convex and $\nabla < 0$ a more concave shape). Furthermore, for other specific shapes (like semicircular or rectangular), this index can easily be computed analytically (see Appendix). Fig. 6 illustrates this feature for the asthmatic patient presented in Fig. 5 (lower two figures).

3) Rectangularity: To quantitatively capture the amount of rectangularity, a definition analogous to the roundness can be employed. In doing so, the TBFV loop has to be normalized, and then, the inscribed and the circumscribed rectangles have to be computed. However, it soon becomes evident that there is an

Fig. 5. Sphericity for a healthy subject (upper two figures). (Left) Original TBFV loop and (right) elucidates roundness after normalization to $\pm 1$. The lower two figures show an asthmatic subject in which expiration does not appear to be particularly “round” ($\circ_{\text{exp}} = 0.32$). TBFV loop is “not round at all” (but does not automatically reveal what shape it has instead). However, when compared to an asthmatic patient (see Fig. 5, lower two figures), it becomes clear that the sphericity is a rather discriminant feature.
Fig. 6. Triangularity for the asthmatic subject presented before. As expected, expiration was classified as being “very triangular,” while inspiration was classified “not triangular at all.”

Fig. 7. Rectangularity features for a patient with (left, upper right normalized) a tracheal stenosis and (normalized, lower right) asthma.

Additional degree of freedom in how to choose the height \( h \) and the width \( w \) of the inscribed rectangle. This problem was solved by setting the area \( A = w \times h \) maximal. By establishing this boundary condition, the expiratory width and height relations are given by

\[
WR_{\text{exp}} = \frac{w_{\text{exp}, \text{inscribed}}}{w_{\text{exp}, \text{circumscribed}}},
\]

\[
HR_{\text{exp}} = \frac{h_{\text{exp}, \text{inscribed}}}{h_{\text{exp}, \text{circumscribed}}},
\] (3)

Two possible ways to quantify rectangularity are to compute the relations of inscribed to circumscribed areas, denoted by \( \blacksquare \), and the summed width and height relations, denoted by \( \Box \). Due to symmetry, it is sufficient to restrict attention to a quadrant. We define

\[
\blacksquare_{\text{exp}} = WR_{\text{exp}} HR_{\text{exp}}
\]

\[
\Box_{\text{exp}} = WR_{\text{exp}} + HR_{\text{exp}}.
\] (4)

Again, the rectangularity features for the inspiration are to be defined in an analogous manner. For an ideal expiratory square, \( \blacksquare_{\text{exp}} = 1 \) and \( \Box_{\text{exp}} = 2 \) would be expected. Fig. 7 shows the results for a patient with a tracheal stenosis and a significant flow limitation during both inspiration and expiration.

Fig. 8. Waviness in (left) laryngeal malacia with inspiratory collapse and (right) tracheal stenosis. The symbol \( \circ \) indicates a found extremum. In the left figure, the inspiratory collapse is correctly identified (\( \sim_{\text{insp}} = 1.418 \)). In the right figure, several extremes are found, but due to the small amplitudes, the shape is not classified as wavy.

Similar to sphericity and triangularity, even for this rather square-shaped TBFV loop neither \( \blacksquare = 1 \) nor \( \Box = 2 \) are reached. However, when comparing stenosis with asthma in Fig. 7, it becomes evident that some diseases are indeed “more rectangular” than others.

4) Waviness: To quantify collapse phenomena in TBFV loops, one possibility is to approximate the normalized loop with high-order polynomials, and then, analytically compute the location of the different extremes of this approximation \( V_{\text{extr}} \). One way to determine the waviness, denoted by \( \sim \), may then be to compute the summed absolute differences in height between the different extremes. For expiration, this leads to

\[
\sim_{\text{exp}} = \sum_{i=0}^{n} |\dot{V}_{\text{breath, exp}}(V_{\text{extr,}[i+1]}) - \dot{V}_{\text{breath, exp}}(V_{\text{extr,}[i]})| - 2
\] (5)

with \( n \) be the number of identified extremes and \( \dot{V}_{\text{breath, exp}}(V_{\text{extr,}[i]}) = 0 \) for \( i = 0 \) and \( i = n + 1 \) due to normalization. For inspiration, the computation is performed analogously. For loops with only one extremum, the waviness \( \sim \approx 0 \). Small oscillations may increase the number of identified extremes, but not necessarily the waviness index because the corresponding amplitudes are small. By contrast, larger collapses will affect \( \sim \) more, as the curve approximation will introduce at least two additional extremes with a large amplitude. Fig. 8 shows the results for two pathologies.

5) Approximation With Polynomials: Another way to analyze TBFV loops is to approximate the normalized loops by low-order polynomials, especially by first- and second-order polynomials. A first-order polynomial is given by

\[
\dot{V}_{\text{breath}} = a_1 \Delta V_{\text{lung}} + b_1
\] (6)

while a second-order polynomial is given by

\[
\dot{V}_{\text{breath}} = a_2 (\Delta V_{\text{lung}})^2 + b_2 \Delta V_{\text{lung}} + c_2.
\] (7)
Here, $\hat{V}_{\text{breath}}$ denotes the optimal approximation of $V_{\text{breath}}$ (performed separately for inspiration and expiration). Using a least-squares (LS) fit, the coefficients $a$, $b$, and $c$ can be found by minimizing the loss function $Q$ as given in the following equation:

$$
\min Q = \sum_{i=1}^{m} (\hat{V}_{\text{breath}}[i] - \hat{V}_{\text{breath}}[i])^2
$$

with $m$ be the number of data points per loop. The following notation will be used, for an approximation with a first-order polynomial, the minimized loss function $Q$ during expiration will be named $Q_{1,\text{exp}}$, while the minimized loss function $Q$ during inspiration for a second-order polynomial approximation will be called $Q_{2,\text{insp}}$. To illustrate the results, Fig. 9 gives the identified coefficients for two examples. Due to

$$
\frac{d\hat{V}_{\text{breath}}}{dt} = 2a_2 \Delta V_{\text{lung}} + b_2 = 0
$$

the coefficients $b_2$ and $a_2$ directly determine the position of the maximum of the approximation. A small $b_2$ seems to indicate symmetry of the loop with respect to the $y$-axis. Also, $a_2 \approx 0$ indicates that the loop is best approximated by a straight line (see Fig. 9, right). Furthermore, the $Q$ values indicate the quality of the approximation and are therefore also considered as features.

### E. Pattern Recognition Using SVMs

A basic aim of this paper was to investigate the suitability of SVMs for this kind of diagnostic support and to evaluate the discriminatory power of the old and the new features in diagnosing breathing problems of infants. Here, the nonlinear SVMs have been created by using Gaussian and polynomial kernels. SVMs create a discriminant function $f(x)$ by using a training dataset $D = \{(x_i, y_i) \in \mathbb{R}^n \times \mathbb{R}, i = 1, \ldots, P\}$, thus consisting of $P$ pairs $(x_1, y_1), (x_2, y_2), \ldots, (x_P, y_P)$, where the inputs $x_i$ are $n$-dimensional vectors, and the labels (or system responses) $y_i$ are discrete values for classification problems going from 1 (healthy patient) to 10 (stenosis of major bronchus) here. The final classifier is given by

$$
y_{\text{out}} = f(x_{\text{in}}) = \sum_{i=1}^{N_{SV}} v_i K(x_i, x_{\text{in}}) + b
$$

where $y_{\text{out}}$ is the output of SVM (which is the value of the function $f$ for a given unknown input $x_{\text{in}}$). $N_{SV}$ is the number of support vectors selected during the training (with $N_{SV} \ll P$). Note that $N_{SV}$ corresponds to the number of neurons in a classic neural network approach. $v_i$ are the weights of the expansion, $K$ is the (scalar) value of a given kernel for a given input $x_{\text{in}}$, and $x_i$ are the training data values selected as support vectors during the training process and they are only used to make a classification decision. The bias term $b$ is an offset parameter determined during training.

As an illustrative example, the particular decision (classification) function created by SVM when a Gaussian kernel function is used is given by

$$
y_{\text{out}} = v_1 e^{-1/2((x_{\text{in}} - x_1)/\sigma)^2} + v_2 e^{-1/2((x_{\text{in}} - x_2)/\sigma)^2} + \ldots + v_{N_{SV}} e^{-1/2((x_{\text{in}} - x_{N_{SV}})/\sigma)^2} + b
$$

where $\sigma$ stands for the so-called shape parameter of Gaussian kernels. If instead a polynomial kernel of order $n$ is used, the classification model is given by

$$
y_{\text{out}} = v_1 (x_1^n x_{\text{in}} + 1)^n + v_2 (x_2^n x_{\text{in}} + 1)^n + \ldots + v_{N_{SV}} (x_{N_{SV}}^n x_{\text{in}} + 1)^n + b
$$

Note that unlike many other classification algorithms that try to minimize either the sum of error squares or some other norm of the errors, SVMs search for the separation boundary that separates the elements of two classes with the largest margin, and the margin is defined as the distance between the classes in input space. A construction of a classification decision function based on the geometry of data points in the input space (and not on the norm of errors in the output, i.e., label and space) is a radical novelty in machine learning. Both a theory of large margin classifiers and the experimental results obtained by using SVMs point to the usually superior performance of SVMs (particularly for the sparse datasets). These properties motivated the applications of SVMs in this paper.

Note also that all the results shown below were obtained based on test data pairs unseen during training. The experimental runs were very strict, and 100 training and testing runs were performed with datasets randomly split into the training sets (90% of the data pairs) and the test sets (10% of the data pairs). This corresponds to presenting average results of ten independent 10-fold cross-validation runs and this is both a very strict and an objective statistical test.

With respect to the aforementioned features introduced, earlier attempts to use pattern-recognition approaches for automated diagnostic support for infants have been reported in, e.g., [29] and [42]. In [21], a multivariate Bayesian classification technique using the statistical software package SPSS [43] was applied. By contrast, within the scope of this paper, univariate SVMs [44]–[46] were used and the results compared to the ones...
TABLE III

<table>
<thead>
<tr>
<th>Disease</th>
<th>Bayes, old best</th>
<th>Bayes, new best</th>
<th>SVM, old best</th>
<th>SVM, new best</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asthma</td>
<td>$6.9/\text{TPEF}$</td>
<td>$5.5/\text{TPEF}$</td>
<td>$4.0/\text{TETI}$</td>
<td>$3.2/\text{C-exp}$</td>
</tr>
<tr>
<td>Bronchitis</td>
<td>$20.6/\text{TPEF}$</td>
<td>$19.7/\text{TPEF}$</td>
<td>$15.1/\text{C-exp}$</td>
<td>$14.3/\text{C-exp}$</td>
</tr>
<tr>
<td>GER</td>
<td>$23.1/\text{TPEF}$</td>
<td>$17.0/\text{TPEF}$</td>
<td>$17.3/\text{TPEF}$</td>
<td>$12.9/\text{C-exp}$</td>
</tr>
<tr>
<td>Mild tracheal malacia</td>
<td>$15.6/\text{TETI}$</td>
<td>$12.1/\text{b}_1$</td>
<td>$6.0/\text{TETI}$</td>
<td>$6.8/\text{C-exp}$</td>
</tr>
<tr>
<td>Severe tracheal malacia</td>
<td>$19.3/\text{TETI}$</td>
<td>$16.4/\text{C-exp}$</td>
<td>$15.3/\text{TPEF}$</td>
<td>$9.7/\text{C-exp}$</td>
</tr>
<tr>
<td>Laryngeal malacia</td>
<td>$11.9/\text{TPEF}$</td>
<td>$5.0/\text{C-exp}$</td>
<td>$5.6/\text{TPEF}$</td>
<td>$2.4/\text{C-exp}$</td>
</tr>
<tr>
<td>Tracheal stenosis</td>
<td>$10.4/\text{TETI}$</td>
<td>$7.5/\text{C-exp}$</td>
<td>$4.0/\text{TPEF}$</td>
<td>$6.0/\text{C-exp}$</td>
</tr>
<tr>
<td>Laryngeal stenosis</td>
<td>$25.4/\text{TETI}$</td>
<td>$17.3/\text{TPEF}$</td>
<td>$12.8/\text{TETI}$</td>
<td>$9.2/\text{b}_1$</td>
</tr>
<tr>
<td>Stenosis of major bronchus</td>
<td>$25.0/\text{TETI}$</td>
<td>$21.7/\text{TPEF}$</td>
<td>$11.6/\text{TETI}$</td>
<td>$12.0/\text{C-exp}$</td>
</tr>
</tbody>
</table>

The table compares the performance of the two methods on selecting the “best” feature using the classical and new features for both the Bayesian classifier and SVM. All data were obtained by classifying disease versus healthy symptoms based on one single feature.

### IV. Conclusion

In this paper, 35 different TBFV-loop features (both 12 classical and 23 newly introduced ones) derived from $n = 195$ spontaneously breathing infants were systematically compared regarding their discriminant power.

As a major result, it was shown that 1) the classical features previously proposed to analyze TBFV loops in infants may not always be optimal in describing loop properties in the diseases presented here. Several new loop features were introduced by the authors which, to some extent, were based on observing how some clinicians currently judge the results in a linguistic manner (e.g., “round,” “triangular,” etc.). Other new features were inspired by mathematical curve modeling (e.g., the linear or parabolic curve approximations). Although some of the classical features performed relatively well, using the new features significantly improved the diagnostic performance in six of the nine pathologies. In addition, it was shown that 2) SVMs further enhance the diagnostic performance (i.e., the classification accuracy) as compared to Bayes’ classifiers; this indicates that both the feature extraction and the classification procedure play an important role in overall diagnostic performance and need to be selected and improved not just individually, but with respect to each other.

There are few more interesting outcomes when classifying healthy symptoms versus disease for all the features (inputs). The error percentages clearly indicate, which diseases are easy to diagnose and which are not. On the specific patient population, diagnosing asthma, mild tracheal malacia, and laryngeal malacia was relatively easy, whereas bronchitis and gastroesophageal reflux diagnoses are much more difficult and prone to higher errors when averaging over all 12 old and 23 new features (out of the 24 new features introduced earlier, $d_1/\text{insp}$ and $b_2/\text{insp}$ turned out to be strongly correlated and one was omitted).

This paper focused on the identification of the most discriminant loop features for a set of selected pathologies. In statistical terms, this is a univariate discrimination. In general, a multivariate classification, which takes into account all available information at the same time should further improve the discriminant capacity of the proposed automated lung diagnostic support system and will be investigated in the future.

From the results of this study, we conclude that the discriminant power of TBFV loops in infants may have been underestimated in the past. Due to its simplicity, the TBFV-loop analysis seems to have potential for broader use, possibly in screening. Keep in mind, however, that our conclusions are based on up to four breath strokes per patient only. Current infant tidal-breathing analysis standards require at least 20 to 30 breaths to cope with interindividual fluctuations and to properly quantify tidal breathing parameters [24]. Therefore, we suggest to further research the robustness of the proposed method.

Despite the relatively large number of patients, some major infant pathologies like cystic fibrosis [47] or BPD [34] were not covered by this study, due to the composition of the patient population available to the outpatient department. There also may be a need to study lung-function in ventilated patients.
like in infants with acute respiratory distress syndrome (ARDS) (see [48]). Thus, it would certainly be worthwhile to study the performance of the new features on a larger database, which includes additional pathologies of interest, and we invite potential collaborators to contact us on this subject.

APPENDIX

TRIANGULARITY OF IDEALIZED GEOMETRIC SHAPES

It is interesting to note that for an ideal semicircular shape, the triangularity feature yields

\[ \nabla_{\text{exp}} = \frac{\pi}{2} - 1 = 0.5705. \]

(14)

Equally, after normalization a perfectly rectangular shape would yield

\[ \nabla_{\text{exp}} = \frac{2}{\pi} - 1 = 1. \]

(15)

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