Computer-aided Classification of Peripheral Obstruction using Impulse Oscillometric Features: A Review[☆]

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Abstract

Currently, there is a need to accurately and timely diagnose asthma in children. Spirometry, which is the most common technique used for its diagnosis, is often unsuitable for small children since it requires to follow exact instructions that usually they cannot perform. The Impulse Oscillometry System (IOS) could be an alternative solution for the asthma diagnosis and control in children since it offers important advantages to this end. These include a test procedure that only requires minimum patient cooperation which makes the IOS a friendly technique for young children. Additionally, it is a validated, objective and reliable technique. The disadvantage for its use consists in the interpretation of its results, they are difficult to understand by physicians since the IOS is highly technical and based on mechanical and electrical concepts with multiple output variables. Hence, the IOS acceptance in the clinical field diminishes. To this end, computer-aided decision systems could help clinicians to strengthen the way that peripheral airway obstruction diseases (such as asthma) in children are diagnosed, monitored and controlled. This paper presents a methodological review of research works related to the computer-aided classification of peripheral airway obstruction using the IOS technique, which is focused but not limited to asthmatic children. The purpose is to understand the current computer-aided classification research works on this matter.

Keywords: Asthma, Lung Function, Computer-aided classification, Impulse Oscillometry, IOS

1. Introduction

Asthma is a major chronic obstructive pulmonary disease affecting around 235 million people on a global scale and it is considered the most common chronic non-communicable disease among children [1]. In 2016, the asthmatic population in the United States (US) was estimated to be 26 million, with children constituting about 6.1 million[2]. Children suffering from this condition are often underdiagnosed and poorly controlled, creating a substantial social and economic burden in terms of a decreased quality of life, increased school absenteeism with work loss for parents, elevated health care expenditures, high rates of hospitalizations and emergency room visits, among others[1, 8, 9, 30, 32]. Regardless of its impact, asthma remains a poorly controlled disease [8].

Asthma causes airway hyper-responsiveness, inflammation, and airway obstruction, with a predominant airflow resistance at the small airways, also called peripheral or distal airways which are the airways with an inner diameter less than 2mm [31, 32, 33]. It could be considered that an early evaluation and treatment of small airways could be even more effective for the timely management of the asthmatic disease. Unfortunately, the assessment of small airways using traditional diagnostic tests is a difficult task [5].

[☆]This document is a collaborative effort

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Spirometry is the most common Pulmonary Function Test (PFT) used by primary medical practitioners to diagnose asthma. However, it is often considered unsuitable for young children since it requires significant cooperation from patients to perform extreme maneuvers for the forced inspiration and exhalation required by this test. It has been demonstrated that when performing spirometry, both pre-school and school-age children have difficulty meeting some of the quality-control criteria to achieve reliable and repeatable results [6, 7]. These challenges may have led this method to be significantly under-used when treating children. It is estimated that only 21% of primary care practitioners consistently use spirometry in the diagnosis of asthma in children and only 8.3% consistently use it for routine monitoring [29]. Therefore, robust quantitative techniques to determine airway obstruction to reliably diagnose and monitor asthma at an early stage are needed. The Impulse Oscillometry System (IOS) could be an alternative solution for the asthma diagnosis and control in children since it offers important advantages to this end. These include a validated, objective and reliable patient-friendly technique that only requires the patient's passive cooperation[10, 11]. The disadvantage of the IOS consists in the interpretation of its results, these are difficult to understand by physicians since the IOS is highly technical and based on mechanical and electrical concepts with multiple output variables which hinders its broad acceptance in the clinical field despite its objectivity. To this end, computer-aided decision systems could improve the utility of the IOS and help clinicians to strengthen the way that peripheral airway obstruction diseases (such as asthma) in children are diagnosed, monitored and controlled. This paper presents a methodological review of research works related to the computer-aided classification of peripheral airway obstruction using the IOS technique, which is focused but not limited to asthmatic children. The purpose is to understand the current computer-aided classification research works on this matter. It also provides an overview of the most common pulmonary function testing features used by the different classifiers of the selected articles for this review, which include Spirometry, IOS and Respiratory Model parameters derived from IOS.

2. Spirometry and its Parameters

Spirometry is a Pulmonary Function Test (PFT) that measures lung function by quantifying the volume and flow of air inhaled and exhaled as a function of time. In other words, it determines how much air can be inhaled and exhaled by an individual, and how fast [34, 35]. This test is highly dependent on patient cooperation since extreme maneuvers such as a maximal forced exhalation after a maximum deep inspiration is required. Spirometry is considered the gold standard for the diagnosis and management of chronic obstructive respiratory diseases such as asthma and Chronic Obstructive Pulmonary Disease (COPD) [31, 35]. FVC, FEV1, and FEV1/FVC are the most important spirometric indices used to assess lung function. These parameters are compared against predicted values based demographic data (age, height, sex, and ethnicity) to determine the severity of airway obstruction [34]:

2.1. Forced Vital Capacity (FVC)

The forced vital capacity (FVC) is the total volume of air that the patient can forcefully exhale in one breath. To obtain this measurement, the patient has to perform a spirometric maneuver to deeply inhale air. Then the FVC is obtained when the patient exhales as long and as forcefully as possible. Values of FVC are measured in liters and are also expressed as a percentage of the predicted values for that individual. [34, 35].

2.2. Forced Expiratory Volume in 1 second (FEV_1)

The forced expiratory volume in 1 second (FEV_1) is the amount of air exhaled during the first second of the FVC maneuver. In obstructive airway diseases (such as asthma), the FEV_1 value tends to be reduced. Values of FEV_1 are measured in liters and are also expressed as a percentage of the predicted values for that individual [34, 35].

2.3. FEV_1/FVC Ratio

The FEV_1/FVC is the ratio of FEV_1 to FVC expressed as a fraction and is used to determine if the pattern is obstructive, restrictive, or normal. A reduced FEV_1/FVC ratio indicates airflow limitation. In children, FEV_1/FVC ratio below 0.90 represents airway obstruction. In adults, the FEV_1/FVC ratio is normally greater than 0.75 to 0.80, smaller values suggest airflow limitation [34, 35, 36, 37].

3. Impulse Oscillometry System and its Derived Parameters

The Impulse Oscillometry System (IOS) is based on the forced oscillation technique (FOT), which measures the mechanical properties of the lungs by using the noninvasive superimposition of air pressure fluctuations applied to the airways over the subject's normal breathing. An essential aspect to be understood is that the IOS graphically displays frequency-dependent curves that are of the utmost importance in the diagnosis of distal obstruction because changes in lung function are evaluated based on the visual interpretation of their shape and magnitude [11]. Consequently, the interpretation of IOS results must be performed by trained physicians who understand the infrastructure and the specifics of the test.

3.1. Impedance (Z)

The IOS uses sound waves to calculate the respiratory impedance (Z) by injecting short impulses of air pressure into the mouth and measuring the consequent air flow at the mouth. Periodic brief pulses (rectangular waves) of pressure oscillations are applied with a fixed period of 200 msec from which a range of frequencies of interest is derived (5, 10, 15, 20, 25 & 35 Hz). The respiratory (pulmonary) impedance (Z) is the sum of all the *resistive* and *reactive* forces that oppose the pressure impulses (oscillations) and are calculated from the ratio of pressure and flow at each frequency [12]. The main components of Z are: resistance (R) and reactance (X).

3.2. Resistance (R)

Resistance is the in-phase component of respiratory impedance and reflects information about the forward pressure of the conducting airways[12]. The resistance at 5 Hz (R5) represents the total airway resistance, and the resistance at 20 Hz (R20) represents the resistance of the large airways. The small airways resistance could be deducted by subtracting R20 from R5 (R5-R20). The larger the difference between R5-R20 is, the greater the peripheral airways resistance is. R5-R20 is also considered an IOS-derived parameter known as the frequency-dependence of resistance (fdR) [12, 14]. For instance, resistance is independent of the frequency in healthy subjects, while for small airway obstruction, the resistance at lower frequencies increases but is unchanged at higher frequencies that do not reach the small airways [15]. In other words, distal obstructive diseases such as Asthma, result in a frequency-dependent increase in resistance at lower frequencies because the pressure signal wave propagating out to the lung periphery (R5) encounters greater resistance than the more proximal higher-frequency (R20) impulse [11]. Figure 1 shows the resistance IOS curves of children with Normal and Peripheral Obstruction conditions.

3.3. Reactance (X)

Reactance is the out-of-phase component of respiratory impedance and reflects the capacitive (C) and inertive (I) properties of the airways. Reactance can be viewed as the rebound resistance, or an echo, giving information about the distensible airways [12]. Because the ability of the lungs to store capacitive energy is primarily manifested in the small airways, reactance at low frequencies can provide important information about the small airways [12]. Unlike resistance, reactance is always frequency-dependent [15]. Peripheral obstruction results in a decrease in the reactance magnitude because the signal returning from the lung periphery to the sensor also has to navigate these same narrowed airways [11]. Figure 2 shows the reactance IOS curves of children with Normal and Peripheral Obstruction conditions.

3.4. Resonant Frequency (Fres) and Area of Reactance (AX)

The resonant frequency (Fres) is the frequency at which the reactance's components: "C" and "I" have the same magnitude, since inertance represents a positive value and capacitance a negative value, with the value of reactance at Fres equal to zero. Fres separates the low-frequency from high-frequency impedance. Respiratory restrictive and obstructive conditions cause the Fres value to be increased; moreover, Fres is usually higher in children and decreases with age [12, 14].

The area of reactance (AX), also known as the "Goldman Triangle" is the area under the curve between 5 Hz and Fres (please refer to figs. 3 and 4). This is a single-magnitude parameter (an index), which comprises the reactance at all frequencies where the capacitance (elasticity of the airways) dominates the inertance. As with reactance at low frequencies, the AX parameter provides important information about small airways obstruction [12, 14].

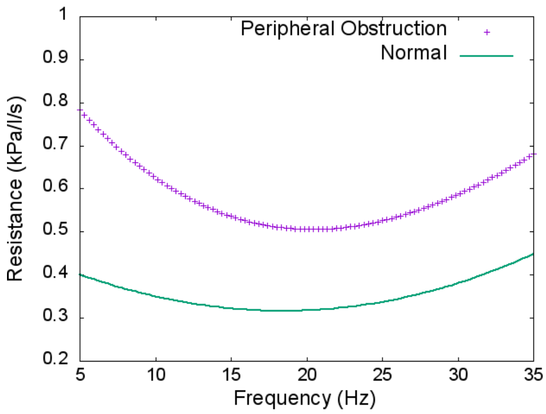

Figure 1: Resistance IOS curves of Children with Normal and Peripheral Obstruction.

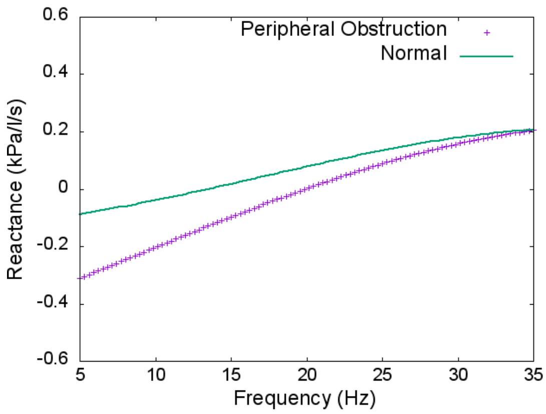

Figure 2: Reactance IOS curves of Children with Normal and Peripheral Obstruction.

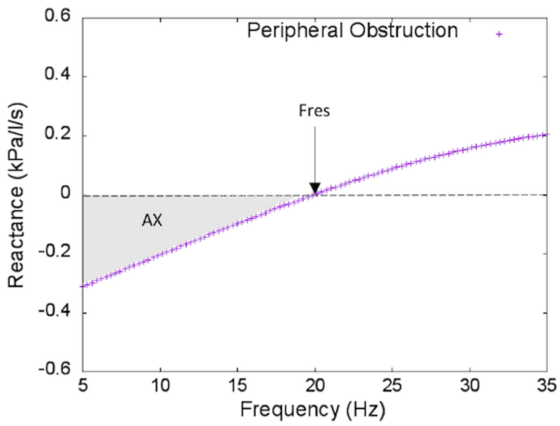

Figure 3: AX and Fres of Children with Peripheral Obstruction.

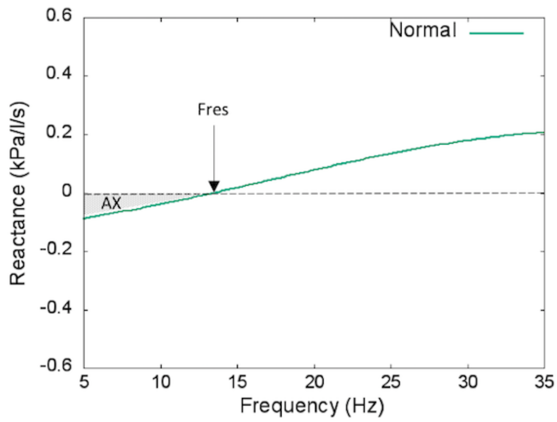

Figure 4: AX and Fres of Children with Healthy Condition.

3.5. eRIC and aRIC Respiratory Model Parameters

The extended Resistance Inductance Capacitance (eRIC) and the augmented RIC (aRIC) are equivalent electrical circuit models for the human respiratory system impedance which are derived from IOS parameters. The eRIC model is an improvement of the RIC model, its components include the representation of large airway resistance "R", peripheral resistance "Rp", large airway inertance "I", and peripheral airway compliance "Cp". Specifically, the added peripheral resistance "Rp" represents the small airways in the respiratory system which could not be captured by the previously developed RIC models. The aRIC model was developed and validated as an augmentation of the eRIC model. The additional element "Ce" in the aRIC model represents the extrathoracic compliance mainly due to the upper airways shunt effects [17]. Figures 5 and 6 show the recent IOS-based equivalent electric circuit models of the human respiratory system.

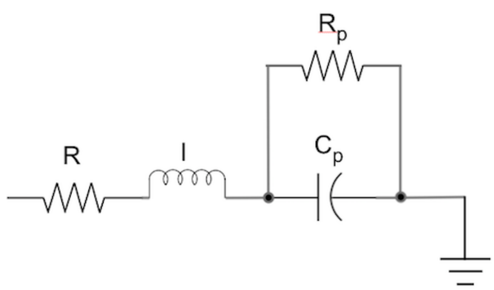

Figure 5: eRIC Model of the Human Respiratory System.

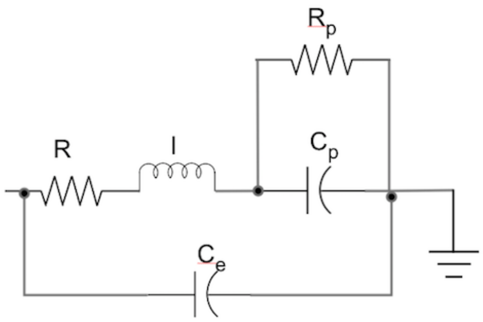

Figure 6: aRIC Model of the Human Respiratory System.

4. Review Methodology

The literature review was performed using the following parameters and databases: "All fields" in PubMed, "Full-Text & Metadata" in IEEE Xplore, and "All Databases" in Web of Knowledge. The search only includes articles written in the English language. The words and logic operators used for the search in each of the databases were "asthma" AND "classification" AND "oscillometry". Additional searches were performed using the same methodology, but substituting in first place the word "asthma" by the phrase "small airways", the next search was done by replacing "small airways" by "peripheral airways", and in the last search "peripheral airways" was replaced by "distal airways". The search was performed on June 29, 2018. A total of 34 articles were found by the search. The title and abstract of these articles were screened and selected based on the following eligibility criteria: 1) Publications centered in the computer-aided classification of asthma or small airway impairment, 2) Computer-aided classification includes Impulse Oscillometry features. Bibliography of selected articles was also screened to find other relevant articles.

5. Computer-aided Classification of Lung Function using Impulse Oscillometry

Of 34 articles identified using web databases, only seven met the eligibility criteria and an additional article was found through the screening of selected articles' bibliography for a total of eight articles.

Based on the selected articles, the most recent research efforts regarding computer-aided classification of lung function using IOS features have been conducted by Badnjevic et al. [18, 19, 20, 21, 22], Hafezi et al. [23], and Barua et al. [25, 24].

Studied conditions, population, classifiers' input features and soft-computing techniques used in the different classification studies are summarized in Tables 1 and 2 and further described in the next sections.

5.1. Studied Conditions

In the selected articles, the conditions studied are Asthma, Chronic Obstructive Pulmonary Disease (COPD), Small Airway Impairment (SAI), Possible Small Airway Impairment (PSAI), Central Obstruction, Peripheral and Healthy conditions. Even though peripheral obstruction related to Asthma and SAI is of our main interest, the results of classification of COPD which is a respiratory condition characterized by chronic airflow obstruction mainly due to long-term smoking [39, 40], are presented because in selected study [21] this condition was studied along with asthma. COPD is not part of the scope of this review; therefore, the works presented in here do not represent all computer-aided classification works using IOS features for this condition.

The classifiers presented by Badnjevic et al. in 4 out of 5 studies [18, 19, 20, 22] were bi-class where the Asthma and Healthy conditions were studied. Study [21] included 3 classes, where COPD was studied along with the Asthma and Healthy conditions.

The classification efforts conducted by University of Texas at El Paso (UTEP) research group includes the work performed by Barua et al. and Hafezi et al. The first two efforts were conducted by Barua et al. in 2004 and 2005 [25, 24]. In both cases, the studies differentiated between 2 classes. In the 2004 classifier, the classes studied were Central and Peripheral diseases, while the classification in 2005 included Asthmatic and Non-asthmatics. The last classification effort by UTEP's researchers was conducted in 2009 by N. Hafezi et al., the classes studied were the Asthma, SAI, PSAI, and Normal conditions.

5.2. Studied Population

Regarding age, Badnjevic et al. in [20] and [21] studied asthmatic subjects with an age range of 19.85 years +/- Standard Deviation (SD) 8.18, while normal subjects were 30.03 years +/- SD 11.83, also in [21] studied COPD patients with a range of 52.25 years +/- SD 7.636, the other studies performed by Badnjevic et al. [18, 19, 22] did not provide information regarding age; in [23] Hafezi et al. studied children from 5 to 17 years old; while the studies performed by Barua et al. included children from 2 to 8 years old in [25] and in [24] subjects studied ranged from 13 to 85 years old. In summary, from the demographics provided by the different studies, only two papers [23] and [25] addressed early childhood, which is considered a critical period to assess pulmonary function since those suffering from asthma usually face the onset of their symptoms during this time [6, 7]. Three papers [20, 21, 24] included subjects in a later childhood stage and adulthood, while the three remaining articles [18, 19, 22] did not provide information about age.

The articles that reported information about gender were [18, 19, 23, 20, 21, 25, 24], these papers included a balanced female and male population, except for [25], where females included the 66.8% of the study while males represented 33.2%. The rest of the studies,[22] and [23] did not include gender information.

The papers published by Barua et al. [25, 24] are the ones that provided more specifics about the demographics of the studied population, they also included subject's information about height and weight. In [25] the subject's height and weight ranged from 0.88 to 1.4 meters and 12 to 32.7 kilograms respectively and in [24] from 1.4 to 1.85 meters and 35 to 176 kilograms respectively.

Most of the papers reviewed provided limited information about the demographics of the studied population. An important aspect is to understand the demographics behind each of the classification studies, as they could play an important role in the performance of IOS acquired values. Particularly, height has been found to strongly correlate with different IOS variables.[38]. Therefore, a comprehensive assessment of anthropometric variables could potentially help to obtain better computer-aided classification results.

A summary of the studied population in each of the selected articles is presented in Table 1

5.3. Input Features and Classification Techniques

In the selected articles, different spirometric and IOS parameters were used as input features of the classifiers presented by the authors. These input features were derived from what are called static and/or dynamic assessments. A static assessment is based on first pulmonary function testing (IOS and/or spirometry). On the other hand, a dynamic assessment of the patient takes into consideration the application of bronchial dilation (BDT) and bronchial provocation (BPT) tests. After BDT and/or BPT treatment and after the second and/or third measurements of pulmonary function, potential changes of lung parameter values are evaluated, from which physicians get accurate information on the specifics of the disease [19, 18, 20, 21].

In the studies reviewed, Badnjevic et al. were the only authors who performed a dynamic assessment in [18, 19, 20, 21, 22] when inconclusive results were obtained with the static assessment. The common input features used in the studies from Bandjevic et al. included the R5, R20, R5-R20, X5 and Fres from IOS; FVC,FEV1, FEV1/FVC from spirometry; along with symptoms and allergy history features; in addition to these features in [18] Bandjevic et al. outlined the use of the PEF spirometric parameter as input feature and in [20] the use of body plethysmography features, while in [19] no specifics about the input parameters used were provided. In these studies, the classification was performed using algorithms based on Artificial Neural Networks (ANN) [18], Fuzzy logic [19] or Neuro-Fuzzy techniques [20, 21, 22], and as previously mentioned most of the classifiers were bi-class.

Studies conducted by N. Hafezi et al. and Barua et al. were based on the static assessment of IOS derived features. N. Hafezi et al. developed two Neuro-Fuzzy multi-class classifiers using IOS parameters R5-R15, AX, and extended model parameters eRIC (R, Rp,I, and Cp), or aRIC (R, Rp,I, Cp, and Ce)[23], in their publication four different degrees of peripheral obstruction were assessed.

On the other hand, Barua et al. studies [25, 24] were based on ANN algorithms were the input features used for the bi-class classification were the IOS parameters R5, R10, R15, R20, R25, R35, and X5, X10, X15, X20, X25, X35 along with demographic features of age, gender, height and weight; and for the particular case of study [24] smoking status features were considered.

The selected studies were based on a supervised training approach for the learning algorithms. An important aspect in the development of learning algorithms is the selection of the relevant features. The process of feature selection also called variables reduction strongly impacts the classifier's performance. In other words, the use of better discriminative parameters will lead to a best classifier's computational and accuracy performance. To this end, none of the studies presented in this review provided a rationale or a method for feature se-

Table 1: Studied Population in Current Research Works of IOS Lung Function Classification

Author	Year	Paper Title	Conditions Studied	Number of Subjects (N)	N per Gender	Age (Years)	Height (m)	Weight (Kg)
A. Badnjević et al	2016	Classification of Asthma Using Artificial Neural Network	Asthma & Healthy	N=1250. Asthma: 728 Healthy: 522	Male: 601 Female: 649	Not reported	Not reported	Not reported
A. Badnjević et al	2016	Diagnostic of Asthma Using Fuzzy Rules Implemented in Accordance with International Guidelines and Physicians Experience	Asthma & Healthy	N=1250. Asthma: 728 Healthy: 522	Male: 601 Female: 649	Not reported	Not reported	Not reported
A. Badnjević et al	2015	Classification of Asthma Utilizing Integrated Software Suite	Asthma & Healthy	N=289 Asthma: 72 Healthy: 217	Male: 142 Female:147	Asthma : 19.85 +/- SD 8.18 Healthy: 30.03 +/- SD 11.83.	Not reported	Not reported
A. Badnjević et al	2015	Neuro-fuzzy Classification of Asthma and Chronic Obstructive Pulmonary Disease	Asthma, COPD & Healthy	N= 455 Asthma: 170 COPD: 248 Healthy: 37	Male: 244 Female: 211	Asthma : 19.85 +/- SD 8.18 COPD: 52.25 +/- SD 7.636 Healthy: 30.03 +/- SD 11.83.	Not reported	Not reported
A. Badnjević et al	2013	Interpretation of Pulmonary Function Test Results In Relation to Asthma Classification Using Integrated Software Suite	Asthma & Healthy	N=156 Asthma: 72 Healthy: 84	Not reported	Not reported	Not reported	Not reported
Nazila Hafezi et al	2009	An Integrated Software Package to Classify Small Airway Impairments of the Human Respiratory System	Asthma, SAI, Mild SAI & Healthy	N=112	Not reported	5-17	Not reported	Not reported
Barúa, Miroslava et al	2005	Classification of Impulse Oscillometric Patterns of Lung Function in Asth- matic Children using Artificial Neural Networks	Asthmatic Constricted & Asthmatic Non-Constricted	N= 361 IOS patterns from 41 subjects. Constricted: 168 Non-constricted: 193	Male: 120 Female: 241	2-8	0.88-1.4	12-32.7
Barúa, Miroslava et al	2004	Classification of Pulmonary Diseases Based on Impulse Oscillometric Measurements of Lung Function Using Neural Networks	Central & Peripheral Diseases	N=131	Male : 64 Female: 67	13-85	1.4 - 1.85	35 - 176

lection. Additionally, the learning algorithms were based in limited soft-computing techniques, particularly only ANN, Fuzzy Logic and Neuro-fuzzy algorithms among the eight selected papers for this review were used.

5.4. Classification Performance

Badnjevic et al. achieved the best classification results in the analysis presented in Table 2; in their studies, the best accuracy results were achieved when using both static and dynamic assessment features, leading to obtain overall classifier's accuracy results ranging from 92.3% to 99.34% in the different studies performed. The best result achieved was in cite badnjeciv2015, where a neuro-fuzzy algorithm was used to classify Asthma, COPD and Healthy conditions. It is important to mention that Badnjevic et al. did not present the overall classifiers accuracy results in their articles, instead they presented the classification performance per class for both static and dynamic assessment approaches, as the authors provided all the information required to calculate the overall classifiers accuracy, we calculated it to be able to compare the different studies, Table 2outlines the condition-specific accuracy results reported by the authors as well as the overall classifiers accuracy calculated by us for both static and dynamic assessment approaches. We need to emphasize that the dynamic assessment used in Badnjevic et al. studies, especially the one derived from the BPT is unsuitable for an important asthma population which is young children. The BPT testing is physically demanding and depends on the patient's ability to perform acceptable spirometric maneuvers, and the patient's fatigue to perform repetitive spirometry testing [26, 27, 28]. Additionally, Badnjenvic et al. used input variables from different sources (IOS and spirometry derived from static and dynamic testing), from both computational and clinical points of view, it is desirable to use the minimum number of sources to perform classification; so parsimony is

Table 2: Results of Current Research Work of IOS Lung Function Classification

Author	Year	Paper Title	Conditions Studied	Diagnostic Techniques Used	Assessment Type	Input Parameters Used	Classification Technique	Accuracy by Condition after Static Assessment			Accuracy by Condition after Static & Dynamic Assessments			Overall Classifier's Accuracy after:		Sensitivity	Specificity
								Asthma	COPD	Healthy	Asthma	COPD	Healthy	Static Assessment	Static & Dynamic Assessments		
A. Badnjević et al	2016	Classification of Asthma Using Artificial Neural Network	Asthma & Healthy	IOS, SPIR, BDT, BPT	Static & Dynamic	**Symptoms** **IOS**: not specified **SPIR:** not specified	ANN	Not reported	Not reported	Not reported	97.11%	N/A	98.85%	Not reported	97.84%	97.11%	98.85%
A. Badnjević et al	2016	Diagnostic of Asthma Using Fuzzy Rules Implemented in Accordance with International Guidelines and Physicians Experience	Asthma & Healthy	IOS, SPIR, BDT, BPT	Static & Dynamic	**Symptoms** **IOS:** R5, R20, X5, R5-R20, Fres **SPIR:** FVC, FEV1, FEV1/FVC , PEF	Fuzzy Logic	8.65 % (63/728)	N/A	89.08% (465/522)	91.89%	N/A	95.01%	42.24%	93.20%	N/A	N/A
A. Badnjević et al	2015	Classification of Asthma Utilizing Integrated Software Suite	Asthma & Healthy	IOS, SPIR, BDT, BPT	Static & Dynamic	**Symptoms and allergy history** **IOS :** R5, R20, R5-R20, X5, Fres **SPIR**: FEV1, FEV1/FVC **Body Plethysmography**	Neuro-fuzzy	11.43% (8/72)	N/A	Not reported	97.22%	N/A	98.61%	Could not be estimated with the information reported	98.20%	98.15%	98.62%
A. Badnjević et al	2015	Neuro-fuzzy Classification of Asthma and Chronic Obstructive Pulmonary Disease	Asthma, COPD & Healthy	IOS, SPIR, BDT, BPT	Static & Dynamic	**Symptoms** **IOS :** R5, R20,R5-R20, X5, Fres **SPIR:** FEV1, FVC, FEV1/FVC	Neuro-fuzzy	87.65% (149/170)	85.5% (212/248)	Not reported	99.41%	99.19%	100%	**86.3%	99.34%	99.28 % (For Asthma & COPD only)	100% (For Asthma & COPD)
A. Badnjević et al	2013	Interpretation of Pulmonary Function Test Results In Relation to Asthma Classification Using Integrated Software Suite	Asthma & Healthy	IOS, SPIR, BDT, BPT	Static & Dynamic	**Symptoms, allergies and risk factors** **IOS** : R5, R20,R5-R20, X5, Fres **SPIR**: FEV1, FVC, FEV1/FVC	Neuro-fuzzy	10.70%	N/A	93.67%	90.25%	N/A	94.04%	51.92%	92.30%	N/A	N/A
Nazila Hafezi et al	2009	An Integrated Software Package to Classify Small Airway Impairments of the Human Respiratory System	Asthma, SAI, Mild SAI & Healthy	IOS	Static	**IOS:** R5-R15, AX eRIC (R, Rp, I,Cp),	Co-Active Neuro-fuzzy Inference System (CANFIS)	Not reported	N/A	Not reported	N/A	N/A	N/A	*95.54%	N/A	N/A	N/A
						IOS: R5-R15, AX, aRIC (R, Rp,I, Cp, Ce)		Not reported	N/A	Not reported	N/A	N/A	N/A	*97.32%	N/A	N/A	N/A
Barúa, Miroslava et al	2005	Classification of Impulse Oscillometric Patterns of Lung Function in Asthmatic Children using Artificial Neural Networks	Asthmatic Constricted & Asthmatic Non-Constricted	IOS	Static	**IOS :** R5, R10, R15, R20, R25, R35, X5 ,X10, X15, X20, X25, X35 **General:** Age, gender, height, weight.	ANN	Not reported	N/A	Not reported	N/A	N/A	N/A	98.61%	N/A	N/A	N/A
Barúa, Miroslava et al	2004	Classification of Pulmonary Diseases Based on Impulse Oscillometric Measurements of Lung Function Using Neural Networks	Central & Peripheral Diseases	IOS	Static	**IOS :** R5, R10, R15, R20, R25, R35, X5, X10, X15, X20, X25, X35 **General:** Smoking status, age, gender, height, weight.	ANN	Not reported	N/A	Not reported	N/A	N/A	N/A	61.53%	N/A	N/A	N/A

* Accuracy of training data. No validation results available.
** Only taking in consideration the Asthmatic and COPD populations as Healthy results were not reported by the authors

favored. As previously mentioned Badnjevic et al. achieved the best results after performing static and then dynamic testing; however, in 3 out of 5 papers, the authors also reported the classification results after performing only static testing, for comparative purposes this is very useful since the rest of the studies involved in this review used input variables derived from static data. To this end, the overall classifier's accuracy results for Badnjevic et al. studies after the static assessment ranged between 42.24% to 86.3%; while Nafezi et al. obtained overall accuracy results on training data (no validation data was used) were 95.54% and 97.32% for the two classifiers described in paper cite; lastly, the overall classification accuracy obtained by Baruas et al. from unseen data in cite 2004 and cite 2005 were 61.53% and 98.61% respectively.

6. Conclusion

To date, different computer-aided classification efforts have been conducted to improve the diagnosis of peripheral obstruction conditions using IOS features. However, these studies are limited regarding the number of publications. According to our research criteria only eight papers were found published from three different main authors. The most recent efforts have been published by Badnjevic et al, with five out of eight publications between 2013 to 2016, followed by one publication from H. Nafezi et al. 2009, and two publications from Barua et al. in 2004 and 2005 respectively. It is worth mentioning that publications are even fewer when specifically talking about the IOS, regarding lung testing features only three papers used only IOS derived features while five used a combination of spirometric and IOS features as the classifier's inputs. To favor parsimony, in this particular case, the use of one source of input variables is more desirable. Regarding asthma, the diagnostic utility of the IOS has a greater impact on children population, as the use of spirometry for this population could provide unreliable results. In this regard, only two articles specifically addressed the children's population. Additionally, one advantage of the IOS over spirometry is that unnoticeable changes in a patient's airway function by the latter may be detected earlier by the former [12], especially because the IOS provides objective information in cases in which spirometry has been either normal or could not have been performed [11]. The areas of opportunities for improvement in the reviewed papers relate to the feature selection approach, as no rationale was provided in any of the articles reviewed to explain why the input features used were chosen or considered relevant, as supervised classification was used by all authors feature selection is an important aspect that impacts the classifier's computational and quality performance. Additionally, another limitation is related to the variety of learning algorithms used by the different authors, only ANN, Fuzzy Logic, or Neuro-fuzzy algorithms were used. Furthermore, In conclusion, there is still a great opportunity to improve the utility of IOS by developing more robust classifiers, specifically for the children asthmatic population as the classification studies performed to date have the following limitations: 1)they are limited in number, 2) they include features derived from tests that are not optimally suitable for children; 3) are bi-class (mostly asthma and non-asthma); or 3) produce modest results for the multi-class classification of the different degrees of peripheral airway obstruction.

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