35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Cough Sound Analysis – A new tool for diagnosing Pneumonia

Abeyratne U R, *Senior Member IEEE,* Swarnkar V, Rina Triasih, Amalia Setyati

***Abstract*—Pneumonia kills over 1,800,000 children annually throughout the world. Prompt diagnosis and proper treatment are essential to prevent these unnecessary deaths. Reliable diagnosis of childhood pneumonia in remote regions is fraught with difficulties arising from the lack of field-deployable imaging and laboratory facilities as well as the scarcity of trained community healthcare workers. In this paper, we present a pioneering class of enabling technology addressing both of these problems. Our approach is centered on automated analysis of cough and respiratory sounds, collected via microphones that do not require physical contact with subjects. We collected cough sounds from 91 patients suspected of acute respiratory illness such as pneumonia, bronchiolitis and asthma. We extracted mathematical features from cough sounds and used them to train a Logistic Regression classifier. We used the clinical diagnosis provided by the paediatric respiratory clinician as the gold standard to train and validate our classifier against. The methods proposed in this paper could separate pneumonia from other diseases at a sensitivity and specificity of 94% and 75% respectively, based on parameters extracted from cough sounds alone. Our method has the potential to revolutionize the management of childhood pneumonia in remote regions of the world.**

I. Introduction

Pneumonia is the leading killer of young children around the world. It accounts for more than 19% of under-five child deaths each year[1]. The vast majority of these deaths occur in resource poor regions of the world such as sub-Saharan Africa, South Asia and remote areas of China and Indonesia. Childhood pneumonia is largely a disease of poverty and is often called the "forgotten disease".

The *definitive* diagnosis of childhood pneumonia, especially the early stage disease, is surprisingly difficult even in a hospital. Lung biopsy may be the most effective approach but it is clearly impractical for clinical use. Clinical examination and chest auscultation with a stethoscope are the first steps in diagnosing childhood pneumonia. Chest X-ray is often used as an important reference standard in confirming a clinical diagnosis. However, X-rays may not be sensitive to early stage pneumonia [2] or when the diseased part of the lung is not clearly visible on the image. X-ray CT imaging (Computed Tomography) and other laboratory analyses such as sputum tests, blood culture and C-reactive protein (CRP) tests may be needed to differentially diagnose pneumonia in some cases.

Unfortunately, let alone advanced technology, even primitive imaging and laboratory testing facilities are beyond the reach for much of the global population. In resource-poor areas of the world where pneumonia is rampant, it is also difficult to find trained healthcare personnel with expert auscultation and clinical skills. Difficulties in the timely diagnosis and proper treatment are the main reasons behind the unacceptably high rate of childhood pneumonia deaths (1.8 million/year [1]) in the world.

In order to address these problems, the World Health Organization (WHO) has developed a simple clinical algorithm to classify pneumonia in resource-limited regions [3]. These classifications directly lead to interventions such as antibiotic prescription and hospitalization. The WHO algorithm uses the symptom of cough (and/or breathing difficulty) as the screening-in feature for pneumonia; breathing rate then determines if pneumonia exists. The disease will be further classified as severe pneumonia if symptoms such as chest recession and stridor are also present. In the past several studies [4-6] have reported varying performance of the WHO algorithm in pneumonia diagnosis with reasonably high sensitivity (69-94%) – it identifies most patients that actually have pneumonia - but poor specificity (16-67%), which means there are many false positives. The poor specificity of WHO algorithm has caused over-prescription of antibiotics wasting rare drug stocks. It also has led to antibiotic resistance [2] in vulnerable communities. Failure to respond to the limited variety of inexpensive antibiotics available in resource-limited regions has also become a serious problem in the prompt and proper treatment of childhood pneumonia.

Two of the critical challenges to be met in managing the global burden of childhood pneumonia are the low diagnostic performance of the WHO algorithm and difficulties in training the large number of workers[7] needed for community healthcare visits. It is known that most deaths from childhood pneumonia occur early in the progression of the disease, and accurate diagnosis and prompt treatment by community health workers may reduce pneumonia mortality by 36-42% [7] in resource-poor regions. Researchers [4-6, 8] have attempted to improve the specificity of the WHO criteria using different approaches. These include the augmentation of WHO algorithm by considering fever [4] and other symptoms of pneumonia (nasal flaring, poor sleep, chest in-drawing, cough lasting longer than two days etc.). These efforts resulted in a sensitivity and specificity within the range 20-90% [4-6, 8, 9], but higher specificities were achieved only at the cost of

This work has been funded by the grant from Bill & Mellinda Gates Foundation, awarded to Dr. Abeyratne.

lower sensitivity and vice-versa. They also suffer from the fact that the higher the complexity of measurements, the more difficult it is to train community workers to reliably implement the algorithm in field visits.

In this paper, we propose a pioneering class of technology addressing these challenges. Our target is to achieve a higher specificity of diagnosis than that of the WHO algorithm while maintaining a high sensitivity.

Cough is a cardinal symptom of pneumonia, but the mathematical analysis of cough has never been used in diagnosing the disease. While cough exists in almost all pneumonia patients, its existence alone is not a specific enough marker of the disease. The vast potential in extracting more information from cough sounds remains virtually untapped in the current diagnosis of pneumonia. In this work we hypothesize that cough carries vital information on the lower respiratory tract enabling us to identify pneumonia-specific features.

Our methods are centered on the analysis of cough and breathing sounds in the diagnosis of pneumonia. The simplest form of the proposed technology does not use sensors that require physical connection with the patient, making it easy to use in the field.

II. METHOD

A. *The development of the cough sound database*

The clinical data acquisition environment for this work is, Respiratory Medicine Unit of the Sardjito Hospital, Gadjah Mada University, Indonesia. The reference standard used for Pneumonia diagnosis is the overall diagnosis provided by physicians, on the basis of clinical presentation, laboratory tests, chest X-ray and the clinical course of the disease.

We collected sound data records from each N=91patient (48 males and 43 females), using bedside microphones (Rode® NT3, 44.1kHz sampling rate). The distance from the mouth to the microphone could vary between 40cm to 70cm depending on the position of the patient's head.

The overall dataset at our disposal was separated into two non-overlapping groups: the *Model Development Dataset* ($\mathbb{D}_{md}$) and the *Prospective Validation Dataset* ($\mathbb{D}_{pv}$). These two datasets were completely independent of each other. $\mathbb{D}_{md}$ and $\mathbb{D}_{pv}$ consisted of N_{md} =66 and N_{pv}=25 subjects respectively.

For the work of this paper we manually segmented out cough sounds after a careful listening process. There is no accepted method for automatic identification of coughs and the manual analysis is still used as the gold standard in clinical work.

B. *Feature Extraction and Pattern Classifier Design*

Let C_{md} be the total number of coughs events from the subjects in $\mathbb{D}_{md}$.

Step-1: Extraction and Augmentation of Cough Features - In this step, we extract mathematical features from cough as follows:

[1]. Let x denotes a discrete time sound signal from an arbitrary cough event.

[2]. Segment x into 'n=3' equal size non-overlapping sub-segments. Let x_i represents the i^{th} sub-segment of x, where i = 1, 2, 3,…., n.

[3]. For each of the sub-segments x_i compute the following features: Bispectrum Score (BGS), Non-Gaussianity score (NGS), the first four formant frequencies (FF), log energy (LogE), zero crossing (ZCR), kurtosis (Kurt), and twelve Mel-frequency cepstral coefficients (MFCC). Note that we do not make use of the 0^{th} coefficient of MFCC, which represents energy in the signal x_i. Please see appendix of [10] for details.

[4]. Repeat steps (i) – (iii) for all C_{md} cough events in $\mathbb{D}_{md}$.

This process leads to a candidate cough feature matrix M_c of the size $C_{md} \times C_f$ for each sub-segment x_i. Where C_f = 63 represents cough based features and C_{md} is the total cough events in database $\mathbb{D}_{md}$.

In the simplest form of the diagnostic algorithm, we will only be using cough-based features to diagnose pneumonia. Inspired by the WHO algorithm that uses age as one of the parameters, we used age in months as a candidate parameter in our models. We also used the presence or absence of fever as a binary variable. In the WHO algorithm, breathing rate is used as the prime parameter in diagnosing pneumonia. In our work, we propose a new measure (see (1)), which we call the Breathing Index (BrI), to capture breathing rate elevations in pneumonia.

$$BrI = \begin{cases} BR - 20 & if\ Age \geq 60\ months \\ BR - 40 & otherwise \end{cases} \qquad (1)$$

In (1) BR is breathing rate and Age is age of the patient in months. While fever is a common symptom of pneumonia, it is not specific to pneumonia. A similar observation holds for the breathing rate. Let $F^c=\{C_f, f_1, f_2, \ldots f_f\}$ represents the Candidate feature set, where C_f represents cough-derived features and the rest denotes augmented features used in our models. Six different feature set was defined as follows: (1) F^1 - C_f (only cough drived features) (2)F^2 - C_f plus BrI (3) F^3 - C_f plus Fever (as binary variable) (4)F^4 - C_f plus Age (in months)(5) F^5 - C_f plus Fever and BrI (6) F^6 - C_f plus Age, Fever and BrI.

[Step 2] Feature Selection and Automatic classifier design - In this paper we used a Logistic-regression model (LRM) as the pattern classifier. The dependent variable Y of LRM is equal to "one" for pneumonic cough and "zero" for non-pneumonic cough. Cough events drawn from a subject with a diagnostic

classification of pneumonia are labeled pneumonic coughs and vice versa. A model is derived using a regression function to estimate the probability Y given the independent cough features (i.e. F^c={C_f, f_1, f_2, …f_f }) as follows:

$$Prob(Y = 1|_{f_1,f_2,f_3,\dots f_F}) = \frac{e^z}{e^z + 1} \quad (2)$$

$$z = \beta_0 + \beta_1 f_1 + \beta_2 f_2 + \cdots + \beta_n f_F \quad (3)$$

To select the optimal decision threshold λ from Y (that the cough is pneumonic if Y is above λ otherwise non-pneumonic) we used the Receiver-Operating Curve (ROC) analysis.

We used a leave-1-out cross validation (LOV) technique for the LRM design. This process was systematically repeated such that each patient in D_{md} was used as the validation data exactly one time. At the end of this process, we end up in N_{md} different LRM models.

Feature Selection: Feature selection is a technique of selecting a sub-set of relevant features for building a robust learning model. We searched for satisfactory set of features using p-value of LRM. Features were selected with p-value less than a threshold value given by p_{ths}. Let C_f^s be the sub-set of selected cough features from C_f and F^c_s be the candidate features set formed by augmenting features with selected cough features.

Once the subset F^c_s is known, we use those features and build a new set of LRMs once again following another leave-one-out validations process.

[Step 3] Selecting a good model from N_{md} LRMs - From the candidate LRMs that use the selected features F^c_s as the input features, we selected one model as the best based on the k-mean clustering algorithm. We selected that model which had the lowest mean square error value with respect to the centroid. Let $\Re^{fc}$ represent the selected LRM and $\lambda_{\Re fc}$ is the corresponding probability decision threshold for a specific combination of features. The model $\Re^{fc}$ is then used as the best model to classify each individual cough event into 'pneumonic-cough' or 'non-pneumonic-cough' groups.

[Step 4] Pneumonic Cough Index (PCI) - In this step, for each N_{md} = 66 patient in the D_{md} we compute a Pneumonic Cough Index (PCI) using the below definition.

Let 'P' be the total number of coughs recorded and analysed from a patient. And let 'Q' out of 'P' coughs are classified as pneumonic cough using selected LRM $\Re^{fc}$ in step 3. Then the PCI index for the patient is computed as

$$PCI = Q/P \quad (4)$$

Then using the ROC analysis we computed a threshold $\boldsymbol{PCI_{th}}$ (optimized for high sensitivity while keeping acceptable specificity) to classify patient into two classes, 'Pneumonia' and 'non-Pneumonia'.

C. *Testing of selected LRM* $\Re^{fc}$ and PCI on D_{pv}

Following the procedure described in section II-B [Step 1] and using the cough events sound data from N_{pv} = 25 patients in dataset D_{pv}, compute the cough event feature matrix M_c^{Dpv} of size $C_{pv} \times C_f$. C_{pv} is total cough events in D_{pv} and C_f = 63 represents cough based features. Form M_c^{Dpv} from M_{fc}^{sDpv} by augmenting clinical features with selected cough features. Use selected LRM $\Re^{fc}$ in Section II-B [Step 3] to classify data in M_{fc}^{sDpv} into classes 'pneumonic cough' and 'non-pneumonic cough'. Then using (4) compute the PCI for each patient in D_{pv}. Applying PCI_{ths} computed in section II-B [step 4] to PCI and classify patients as 'Pneumonia' if PCI>PCI_{th} and 'non-pneumonia' otherwise. Compare the results of automatic classification by PCI with that of attending clinician.

III. RESULTS

A. *Database and clinical diagnosis*

The mean age of the N= 91subjects was 3 years and 1 month (standard deviation 3 years and 11 months). The age range of the subjects varied from 1 month to 15 years. Of the 91 subjects, 63 were Pneumonia patients and 28 were non-pneumonia patients. Non-pneumonia patients had diseases such as Asthma, Bronchitis, Rhinopharyngitis and others (wheezing, tonsilopharyngitis, heart disease, foreign body inhalation).

B. *Pneumonia diagnosis based on WHO criteria*

Table I show the contingency table for Pneumonia diagnosis using WHO criteria and clinically diagnosed Pneumonia. WHO guidelines for pneumonia diagnosis in community settings are designed for children with age group of 2 months to 5 years[7]. Therefore Table I is generated using #68 subjects in our database, which falls in the age range 2 months to 5 years. WHO criteria achieved a high sensitivity of 83% in picking clinically confirmed pneumonia cases, however presented with a poor specificity of 47%.

C. *Pneumonia diagnosis using designed model*

In section II-A, we divided N=91 patients into two datasets D_{md} (Training/Validation dataset) and D_{pv} (Prospective study dataset). D_{md} has data from N_{md} = 66 patients with C_{md} = 440 cough events (average = 6.7±2, minimum = 2, maximum = 12). D_{pv} has data from N_{pv} = 25 patients with C_{pv} = 159 cough events (average = 6.4±1, minimum = 5, maximum = 10).

From N_{md} =66 designed LRMs for each F^c_s using data from D_{md}, robust model $\Re^{fc}$ was selected using k-mean clustering method as discussed in section II-B [Step 3]. The chosen model $\Re^{fc}$ and all its parameters were fixed for use in step [4] of section II-B. Using the definition given in section II-B [Step 4], PCI index was computed

for each patient. By ROC analysis a PCI_{th} was selected and applied on PCI to classify patients into 'Pneumonia' and 'non-Pneumonia'. Table II shows the PCI based pneumonia/non-pneumonia classification results for 6 feature combinations F^c_s on training/validation dataset. All the feature combinations achieved a sensitivity and specificity greater than 90% except for F^3_s which registered a slightly lower specificity of 86% . F^1_s which uses only cough features has the sensitivity of 93% and specificity 90.5% with K=0.83.

The model $\Re^{fc}$ selected in section II-B [Step 3], was tested on completely new dataset D_{pv} consisted of N_{pv} = 25 patients. Model was tested for both, performance in classifying cough events into pneumonic and non-pneumonic cough and in separating the patients with pneumonia from non-pneumonic using PCI.

TABLE I
COMPARISON OF PNEUMONIA DIAGNOSIS BASED ON WHO CRITERIA AGAINST CLINICAL DIAGNOSIS.

WHO criteria. [Cough and/or breathing difficulty] Threshold for fast breathing 2 – 11 months – 50 BPM 12 – 60 months – 40		**Clinical Diagnosis**		
	WHO Diagnosis		**Pneumonia**	**Non-Pneumonia**
		Pneumonia	44	8
		Non-Pneumonia	9	7

For cough classification, model $\Re^{f6}$ (selected cough features along with presence of fever, Age and BrI) achieved the best classification with sensitivity = 88% and specificity = 85%. $\Re^{f1}$ which used only cough features has sensitivity and specificity of 83% and 58% respectively. In separating pneumonia and non-pneumonia patients, top performing model was $\Re^{f3}$ which uses cough features and fever, with kappa agreement of 0.82, almost perfect agreement. $\Re^{f1}$ which uses cough only features achieved a high sensitivity and specificity of 94% and 75% respectively. Table III shows the performance of the selected LRM $\Re^{fc}$ in classifying patients into pneumonia and non-pneumonia.

IV. CONCLUSION

In this paper we proposed an automated algorithm to diagnose pneumonia using cough sounds. The method is based on initially classifying individual cough events into 'pneumonic cough' and 'non-pneumonic cough' classes and then calculating a Pneumoic Cough Index (PCI) over all the cough events recorded. Working on 599 cough events from 91 pediatric patients diagnosed with a range of respiratory diseases, we showed that our method is capable of classifying pneumonia at a sensitivity >90% while holding the specificity at >85%. The simplicity of proposed technology and potential low cost implementation on ubiquitous devices make our approach valuable in long term monitoring. It also will have substantial strategic value in developing new vaccines as well management strategies for childhood pneumonia.

TABLE II
PERFORMANCE OF THE SELECTED LRM $\Re^{fc}$ ON D_{md} IN DIAGNOSING PNEUMONIA USING PCI.

Selected LRM	**PCI_{ths}**	**Sens**	**Spec**	**PPV**	**NPV**
$\Re^{f1}$	0.5	93%	90.5%	95%	86%
$\Re^{f2}$	0.5	93%	90.5%	95%	86%
$\Re^{f3}$	0.5	91%	86%	93%	82%
$\Re^{f4}$	0.5	91%	91%	95%	83%
$\Re^{f5}$	0. 5	93%	90.5%	95.5%	86%
$\Re^{f6}$	0.67	91%	90.5%	95%	83%

TABLE III
PERFORMANCE OF THE SELECTED LRM $\Re^{fc}$ ON PROSPECTIVE DATASET D_{pv} IN DIAGNOSING PNEUMONIA USING PCI.

Selected LRM	**Sens**	**Spec**	**PPV**	**NPV**
$\Re^{f1}$	94%	75%	89%	86%
$\Re^{f2}$	82%	63%	82%	63%
$\Re^{f3}$	94%	87.5%	94%	88%
$\Re^{f4}$	94%	75%	89%	86%
$\Re^{f5}$	88%	75%	88%	75%
$\Re^{f6}$	82%	100%	100%	73%

REFERENCES

[1] WHO/UNICEF, "Global action plan for the prevention and control of pneumonia (GAPP)," vol 23, 2009.

[2] Z. A. Bhutta, "Childhood pneumonia in developing countries: Refinement of clinical algorithms is a priority," *BMJ,* vol. 333, p. 612, 2006.

[3] "IMCI Integrated management of Childhood Illness," *World Health Organization,* 2005.

[4] M. R. A. Cardoso, C. M. Nascimento-Carvalho, F. Ferrero, F. M. Alves, and S. N. Cousens, "Adding fever to WHO criteria for diagnosing pneumonia enhances the ability to identify pneumonia cases among wheezing children," *Archives of disease in childhood,* vol. 96, p. 58, 2011.

[5] M. Harari, V. Spooner, S. Meisner, M. Carney, F. Shann, and J. De Campo, "Clinical signs of pneumonia in children," *The Lancet,* vol. 338, pp. 928-930, 1991.

[6] M. Palafox, H. Guiscafré, H. Reyes, O. Muñoz, and H. Martínez, "Diagnostic value of tachypnoea in pneumonia defined radiologically," *Archives of disease in childhood,* vol. 82, pp. 41-45, 2000.

[7] Tessa Wardlaw, E. W. Johansson, and M. Hodge, "Pneumonia: The forgotten killer of children," *UNICEF/WHO,* 2006.

[8] J. Lozano, M. Steinhoff, J. Ruiz, M. Mesa, N. Martinez, and B. Dussan, "Clinical predictors of acute radiological pneumonia and hypoxaemia at high altitude," *Archives of disease in childhood,* vol. 71, pp. 323-327, 1994.

[9] E. Mulholland, E. Simoes, M. Costales, E. McGrath, E. Manalac, and S. Gove, "Standardized diagnosis of pneumonia in developing countries," *The Pediatric infectious disease journal,* vol. 11, p. 77, 1992.

[10] V. Swarnkar, U. Abeyratne, A. Chang, Y. Amrulloh, A. Setyati, and R. Triasih, "Automatic Identification of Wet and Dry Cough in Pediatric Patients with Respiratory Diseases," *Annals of Biomedical Engineering,* vol. (Accepted for publication 2013), 2013.