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HESSENBERG ELM AUTOENCODER KERNEL FOR DEEP LEARNING

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Abstract

Deep Learning (DL) is an effective way that reveals on computation capability and advantage of the hidden layer in the network models. It has pre-training phases which define the output parameters in unsupervised ways and supervised training for optimization of the pre-defined classification parameters. This study aims to perform high generalized fast training for DL algorithms with the simplicity advantage of Extreme Learning machines (ELM).

The applications of the proposed classifier model were experimented on RespiratoryDatabase@TR. Hilbert-Huang Transform was applied to the 12-channel lung sounds for analyzing amplitude-time-frequency domain. The statistical features were extracted from the intrinsic mode function modulations of lung sounds. The feature set was fed into the proposed Deep ELM with the HessELM-AE. The proposed model was structured with 2 hidden layers (340,580 neurons) to classify the lung sounds for separating Chronic Obstructive Pulmonary Disease and healthy subjects. The classification performance was tested using 6-fold cross-validation with proposed Deep. HessELM-AE has achieved an influential accuracy rate of 92.22% whereas the conventional ELM-AE has reached an accuracy rate of 80.82%.

Keywords: Deep learning, RespiratoryDatabase@TR, COPD, lung sounds, deep ELM, Hessenberg decomposition.

1. Introduction

Machine learning (ML) algorithms are the most popular research areas for computer engineering demanding on necessity for the accurate fast learning kernels. ML merges computer engineering and statistic models. The ML focuses on real-world problems with artificial neural network which is projected for decision-making on new situations demanding similar ones. The learning procedures on the ML create statistical models and optimizes the network parameters for making a better pattern prediction and recognition in data. Especially, the nonlinear classifier models for computer vision, object recognition, image processing and time-series signals have accelerated the developments for deeper and detailed analysis of big data. Artificial intelligence was the most spectacular approach with similarities on the modeling the human brain and learning procedure in last decades [1]. With the augmentation of the data and the need of generating the knowledge from the information have given a path to the deeper analysis and raising learning capabilities of machine learning algorithms. In recent years the most capable learning algorithm is Deep Learning (DL) which is born from the idea of detailed artificial intelligence idea [2].

The biggest advantage of the DL is supporting both feature learning including feature extraction and classification stages with many hidden layers. The DL is a complex neural network model with many hidden layers and big size of neuron numbers in each hidden layer. The point that differentiates the DL against neural network model is possessing of unsupervised learning in the pre-definition of the classification parameter instead of randomness [2], [3]. The DL algorithms differ at the pre-definition of the model using various unsupervised kernels such as autoencoder, sparse autoencoder, contrastive divergence, stack autoencoder, restricted Boltzmann machines, and more. The rise of DL has been corroborated by recent advanced technologies, specially the efficient and high capable parallel processing in CPUs and GPUs. The weakest specification of the conventional DL is long training time for the real-world problems even when also using GPUs. In future works, accelerating the learning and recognition speed with algorithms and machine powered hardware technologies will be the prominent interest of the DL before increasing the accuracy performance, in the meantime object recognition models have reached achieving about accuracy rate of 98% in image processing [4].

Auscultation is a basic physical examination method which is based on listening inner body parts with a stethoscope. The auscultation sounds are not hearable sounds without tools. In contrast with the simplicity of the method, it is still the most used diagnostic tool for respiratory, cardiac and cardio-pulmonary diseases [5]. The stethoscope provides listening sounds from heart, lungs and gastrointestinal parts. Whereas the cardiac auscultation sounds are based on specified areas on the back and chest, pulmonary auscultation areas are not certain points for the disorders demanding of the structure of the lungs. The history of the stethoscopes started with a basic wooden pipe, and recent developments on the stethoscopes has provided getting and also recording clear and adventitious sounds by digital stethoscopes. The adventitious auscultation sounds are very important for differential diagnosis in medicine. The recent digital stethoscopes have ability to amplify the adventitious auscultation sounds in various filters and levels for eliminating experience-based faults of physicians [5], [6]. In spite of the developments on biomedical devices and diagnostic tools in medicine, the auscultation and pulmonary function test are still the simplest and the most influential method for diagnosing the respiratory diseases.

Lung sounds are the most common type of the auscultation sounds which are heard on chest and back. Lung sounds are used to detect the state of the airways in lung parts. The state of the lung airways and the obstructions in the bronchus are the main symptoms of the respiratory diseases [7]. The breathing results vibrations on the lung walls and bronchus. The vibrations and air circulation during breathing turn into the lung sounds. The elasticity, thickness of the walls and obstructions, mucus in the airways compose various types of lung sounds. The pathological sounds are heard as wheeze and crackles which are audio-visual forms for the pulmonary disorders and every so often cardiac disorders [8].

Chronic Obstructive Pulmonary Disease (COPD) is a group of diseases that include emphysema and chronic bronchitis. It is a progressive and not fully reversible and curable, but preventable and treatable lung disease. The main reason of the COPD is smoking for many years and chemical dusty working environment [9]. It causes much of the discomfort for patients with narrowing airways and airflow in the lungs symptoms. Inspiration and exhalation problems and coughing with mucus are usually progressive for advanced levels of the COPD [10]. Hereby the COPD is not a curable disease, the diagnosis of the COPD is mandatory to control the disease in the severe levels.

Wisniewski et al. proposed a diagnosis model for chronic lung diseases including the COPD. They analyzed 246 lung sounds by wavelet decomposition transform at different levels and pointed Daubechies 6th level sub-band features as the most responsible features for chronic lung diseases [11]. Amaral et al. focused on the clinical parameters and spirometry test measurements and its application on artificial neural network for discriminating the COPD patients [12]. Ying et al. statistically analyzed respiratory questionnaire results, physical examination status, spirometry measurements for separating different COPD levels using an integrated model of Deep Belief Networks (DBN) [13]. Altan et al. performed a COPD severity classification model using a quantization model on lung sound visualizer plot with the DBN classifier model [2].

In this study, considering the importance of the diagnosis of COPD, the 12-channel lung auscultation sounds from RespiratoryDatabase@TR were analyzed using Hilbert-Huang Transform (HHT) and the statistical features were evaluated for classification of the COPD patients and healthy subjects. We aimed to proposed a DL kernel for Deep Extreme Learning Machines (Deep ELM) kernel as an alternative to the traditional Deep ELM kernel by Kasun et al [14] to accelerate the training speed and to improve the generalization performance for the simple and complex structured network models using simple matrix inversing capability of the Hessenberg decomposition technique.

The paper is organized into multimedia respiratory database which is called as RespiratoryDatabase@TR, HHT in detail, structure and mathematical model of the Deep ELM, and the proposed Hessenberg decomposition Deep ELM autoencoder kernel. The experimental results of the proposed Hessenberg Deep ELM autoencoder on diagnosis of the COPD are evaluated in following sections.

2. Materials and Method

The section contains detailed information about RespiratoryDatabase@TR which is a unique multimedia respiratory database and data acquisition process, applying HHT to lung sounds, statistical feature extraction from the modulated frequency bands and classification algorithms.

2.1 Database

Lung sounds are the main markers of the respiratory diseases for a steady diagnosis. In the cases which is not certain with the lung sounds, pulmonologist and cardiac physicians use additional diagnostics such as chest X-ray, pulmonary function test, and rarely heart sounds. The RespiratoryDatabase@TR is a unique multimedia respiratory database. It is based on the chronic pulmonary diseases and cardiac diseases. The main focus point of the RespiratoryDatabase@TR is principally COPD [15]. The RespiratoryDatabase@TR contains 12-channel lung sounds from different auscultation points of the subjects, 4-channel heart sounds from intercostal cardiovascular points. The database is also supported by St. George Respiratory Questionnaire for COPD (SGRQ-C) answer; chest X-rays, and pulmonary function test (spirometry). The chest X-rays are able to use for image processing techniques for computerized analysis. The SGRQ-C answers are collected to assess the labelling the lung sounds in addition as deterministic measurements. The lung sounds and heart sounds support digital signal processing on time series and developments on diagnosis of the respiratory diseases. Pulmonary function test metrics including Tiffeneau-Pinelli index, forced expiratory volume (FEV), forced vital capacity (FVC), and more are the most important measurements for respiratory status for the patients. These measurements are utilized for the exact diagnosis of the chronic pulmonary diseases. The auscultation sounds from RespiratoryDatabase@TR are recorded using two digital stethoscopes by a pulmonologist in parallel of left and right foci points. They were pre-processed using a designed medical interface for segmentation and synchronizing for computerized analysis.

In this work, 12-channel lung sounds are utilized for the separating the COPD patients from the healthy subjects. The lung auscultation areas on back and chest are depicted in Fig 1. The lung sounds have various lengths on RespiratoryDatabase@TR. The 10s of segments from the beginning of the recordings were extracted from lung sounds. The analysis is focused on 15 patients with COPD and 15 healthy subjects.

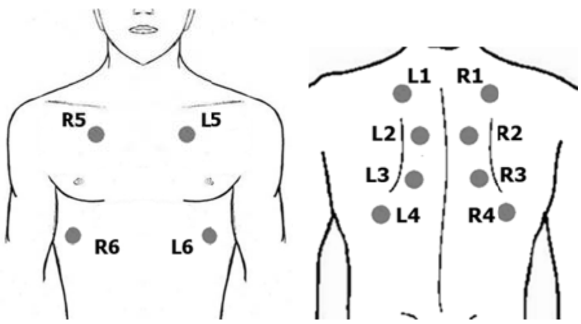

Figure 1. The standardized lung auscultation areas on body

The lung sounds from right (R) and left (L) foci points were acquired synchronously using two digital stethoscopes. The patients were asked to cough at the beginning of the recording for obtaining a triangulation point to use it in the synchronization. The pre-processing steps including synchronization, 10s segmentation and labelling of the auscultation sounds were enforced using designed computer medical interface. The utilized digital stethoscopes have filtered the ambient sounds using special rubber equipment. They can amplify the adventitious vibrations from inner body that are severely heard using acoustic stethoscopes using different filters which represent for the different sides of the stethoscope diagram. The bell filter applied lung sounds were analyzed in the experiments for separating the COPD from the healthy subjects.

2.2 Hilbert-Huang Transform

The HHT is an influential transformation algorithm which may handle non-linear and non-linearity signals. The HHT is a favorite signal analysis method in the feature extraction, filtering, and pre-processing steps of the ML. It may extract energy-time-frequency distributions in different signal modulations. The most powerful course of the HHT is that, its theory is still empirical and is not completed [16]. Considering the empirical statue of the HHT, adapting the novel approaches and ML algorithms is recent researches. The HHT is comprised of Empirical Mode Decomposition (EMD) which has sifted signal modulations from the signal for analyzing time domain, and the Hilbert Transform (HT) which has applied for non-stationary problems for analyzing the signal in frequency domain [17], [18].

1) *Empirical Mode Decomposition:* The EMD starts by pointing out minima and maxima points in the signal. The obtained extrema points were splined as maximum and minimum envelopes [19]. The mean envelope of the signal at any t time needs to be a monotonic function to extract signal modulations. Monotonic function represents for the signal which has at most one extremum or the standard deviation in the signal handles to a very small number for the sifting process. If the obtained mean envelope meets the expectations of the monotonic function, the signal modulation that is called as Intrinsic Mode Function (IMF) is extracted from the signal else the sifting process continues in the same modulation [17], [18]. r_n is the residual signal, $x(t)$ is the input signal, and n is the number of obtained the IMF.

$$x(t) = r_n(t) + \sum_{j=1}^{n} IMF_j(t) \tag{1}$$

2) *Hilbert Spectral Analysis:* The extracted IMFs have also the frequency modulations. The HT decomposes instantaneous frequency meaning of each period. The HT extracts the amplitude-frequency-time description of the IMFs in HHT process [16]. ω is instantaneous frequency function, $\Re$ is the real part of the complex function. Considering the ω of the signal $x(t)$ at any *t* time, the analytic function of the HHT can be defined as follows

$$x(t) - r_n(t) = \Re\left[\sum_{j=1}^{n} A_j(t) e^{i\int \omega_j(t)dt}\right] \tag{2}$$

2.3 Deep Extreme Learning Machines

Extreme Learning Machines (ELM) is modelled as a simple neural network model with a single hidden layer. The learning capability of the ELM was approved by Huang in 2004 [20]. The ELM kernel is utilized for classification and regression solutions by Singular Value Decomposition which is a simplistic inversing solution. The ELM has a fast learning algorithm for the single neural network model. It is an efficient decomposition technique with randomly defined classification parameters and determining output weights of the model (β) using principal inversing solutions [21]. In the mean while the same structure, optimization using optimizing the model with Eigen vector determinations is the fundamental disparity for the ELM.

Analyzing the input parameters in detailed structure is impossible with single hidden layer, it is necessary to enhance the model of the ELM with many hidden layers. To transfer the fast training capability and high generalization capability to the DL algorithms, Deep ELM model was proposed by Kasun et. al in 2013 [14]. The Deep ELM is comprised of unsupervised ELM autoencoder algorithm and supervised ELM learning steps, respectively [22].

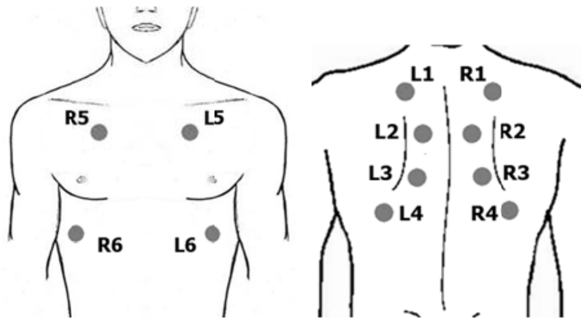

Figure 2. ELM Autoencoder

The ELM autoencoder generates different presentations of the input by calculating hidden node parameters by using input as also output of the autoencoder (Figure 2). The number of the nodes in hidden layer is set to the Deep ELM model hidden layer numbers, separately. Afterwards calculating β by ELM autoencoder, the last layer of the Deep model is structured as the supervised ELM procedure. Generating different presentations provides feature learning on each hidden layer on the Deep ELM network.

1) *The proposed ELM-AE with Hessenberg Decomposition:* The conventional ELM autoencoder (ELM-AE) kernel is solved using Moore-Penrose matrix inversing on singular value decomposition (SVD) technique. The Hessenberg decomposition is an efficient way to inverse square matrix. In this study, we suggested ELM-AE with the Hessenberg decomposition (HessELM-AE) kernel as an alternative to the SVD. If we assume the β parameters, H vector as the hidden nodes, C is a sparsity parameter, and X as the output and input of ELM-AE:

$$\beta = H^T \left(\frac{I}{C} + HH^T\right)^{-1} X \tag{3}$$

Hessenberg decomposition is a matrix inversing technique which is proposed for a real symmetric and square matrix [23]. The technique solves A into a unitary matrix P and a tri-diagonal symmetric Hessenberg matrix H for enhancing the performance of the model for Deep ELM models using simple matrix inversing capability.

$$P\ H\ P^H = A \tag{4}$$

P^H represents for the conjugate transpose. The H matrix can be solved using simple analytic mathematical solutions considering (4) in HessELM-AE. The calculated H matrix is transferred as the output weights for the Deep ELM with HessELM-AE kernel.

2. Experimental Results

The lung sounds were segmented with 10s window to set the signals to same length for HHT signal analysis. The recordings from COPD patients and healthy subjects were selected in same numbers for handling the homogeneity in the subject distribution in the experiments. The experiments were evaluated in a limited number of neuron sizes and hidden layer size. The HHT decomposition and time-frequency-amplitude distributions of the IMF modulations were statistically analyzed and the classification performances including accuracy, specificity, and selectivity were evaluated.

The researches on early diagnosis of COPD by distinguishing healthy lung sounds and pathological lung sounds, and detecting different severities of the COPD are the pioneer approaches in signal analysis. The literature usually focuses on cardiac diseases using ECG [8], [24], [25], neurological disorders using EEG [26], disabled activities using EMG. It is a recent area analyzing musical characteristic auscultation signals including lung, tracheal, vesicular, and bronchial sounds for detecting abnormalities on respiratory and cardio-pulmonary diseases. It has taken a great importance by placing the COPD in the deadliest list of the world. The proposed Deep ELM with HessELM-AE kernel was evaluated on COPD diagnosis using the HHT based amplitude-time-frequency characteristics. 10s of segmented lung sounds were utilized in the analysis considering at least two breathing cycles. The statistical features of the HHT-based IMF modulations were counted as feature set. In the consequence of various number of IMFs from the signals, IMF1 to IMF5 modulations were determined. The statistical classification performance measurements were assessed from the contingency table of Deep ELM with HessELM-AE kernel.

12-channel lung sounds from RespiratoryDatabase@TR were included in the diagnosis analysis. The COPD has five severities considering the symptoms and spirometry measurements of the patients. The COPD population has selected 15 of COPD patients in which 3 patients from each level of the COPD. COPD0 is the closest specifications with the healthy auscultation sounds who has none of physical disability expect smoking. The other COPD severities has increasing disabilities and pathological wheezing during respiratory. 15 healthy subjects were selected among the people who have never used any tobacco products and have no diagnosed chronic lung disorder. A total number of 360 lung sounds were evaluated for COPD analysis by Deep ELM with HessELM-AE. The HT was applied to each IMF modulation after extracting IMFs by EMD.

The statistical and power features were calculated from each HHT-based IMF modulation. The feature set consists of 12 features such as mean, median, standard deviation, max, min, variance, mode, kurtosis, moment, cumulant, power and energy of the $IMF_{1\text{-}5}$ modulations except the residual signal and $IMF_{6,7}$.

The experimented Deep ELM networks with HessELM-AE and conventional ELM-AE were structured from 2-3 hidden layers. The number of neurons in each hidden layer was experimentally selected at a range of 60 to 500 neurons. The sparsity parameter for Deep ELM-AE kernels was selected so small (0.001). The classification performances for each Deep ELM model were evaluated using 6-fold cross validation technique and the best measurements were compared.

Table 1. Classification performances (%) of the Deep ELM kernels on entire IMF feature sets.

Deep ELM	Accuracy	Sensitivity	Specificity
HessELM-AE	68.61	71.67	65.56
Conventional ELM-AE	64.17	66.67	61.67
HessELM-AE with IMF selection algorithm	92.22	89.44	95.00
Conventional ELM-AE with IMF selection algorithm	80.83	88.89	72.78

The Deep ELM with HessELM-AE which was the best performance was structured with three hidden layers, 360-270-180 neurons in hidden layers, respectively. The lung sounds with the COPD and healthy lung sounds can be separated with high classification performance rates of 68.61%, 71.67%, and 65.56% for overall accuracy, sensitivity, and specificity, respectively using statistical features from entire IMFs. Since the various number of IMFs, it is necessary to determine the highest responsible IMF modulation features by adapting feature selection algorithms to IMF selection process. The sequential feature forward selection algorithm was adapted to find state the best features and increasing the classification performance. When the classification was performed for each IMF modulation features as a feature set, the three highest responsible IMFs are IMF_5, IMF_3, and IMF_4 in a sequence. IMF selection algorithm effect the model as an increase in performance rates of 92.22%, 89.44%, and 95.00% for accuracy, sensitivity, and specificity, sequentially. The lowest responsible feature is IMF_1 with the Deep ELM classifier with HessELM-AE. The Deep ELM with conventional ELM-AE was performed on the same experimental setup. The Deep ELM with conventional ELM-AE has achieved the highest classification performance with two hidden layers, 340-580 neurons in each layer, respectively. The achieved classification performances on entire IMF features are 64.17%, 66.67%, and 61.67% for accuracy, sensitivity, and specificity, respectively. The classification performance is augmented to 80.83%, 88.89%, and 72.78% using IMF selection algorithm. The highest responsible IMF is IMF_3, and lowest responsible feature is IMF_1 using Deep ELM with conventional ELM-AE.

4. Conclusion

The respiratory sounds are effective diagnostic method for detecting respiratory diseases. The detailed assessment of the pathological variations and wheeze on lung sounds is an essentialness for upgrading treatment processes and disorder management processes. The instantaneous pathological changes on respiratory sounds effect signal in frequency-time domain. The analysis on frequency domain has ability to extract significant characteristics of the lung sounds. The HHT is an efficient way to perform frequency-time-amplitude specification of the biomedical signals. The extracted IMF modulation based features had differentiated healthy lung sounds from pathological ones. The study is of great importance on the grounds of it is one of the pioneer studies on COPD diagnosis using computerized lung sound analysis on the DL. The merging the HHT-based statistical features, the proposed Deep ELM with HessELM-AE kernel and the RespiratoryDatabase@TR has provided enhancing revolutionizing classification performances and upgrading computerized training algorithms.

IMF modulations carry different frequency range specifications. In the experiments, the IMF1 which is extracted from 10s lung sound is the lowest responsible feature for the COPD diagnosis using Deep ELM kernels. The reason of the fact that the IMF_1 is usually qualified as the noisy modulation for the distributions [18].

The COPD is a fatal condition that limits the life quality and social life with bedridden. The cases of the COPD including incurability and just controllability in the diagnosed severe make the early detection of the disease and starting the treatment in early so significant for preventing the prevalence. Supportive deterministic diagnostic tools for the COPD including spirometry measurements, chest X-ray, and the clinical parameters are time consuming operations, but they result much lose time to apply. It is also dependent to well-experienced pulmonologist clinicians. The proposed model has ability to separate the COPD patients and healthy subjects using 10s auscultation sounds. It is a big step to develop diagnosis-early diagnosis models for small and medium-budget health institutions.

The proposed HessELM-AE has improved the generalization capacity of the Deep ELM against the ELM-AE. The mathematical simplicity of the Hessenberg decomposition enhances generating significant and meaningful representations of HHT-based features on lung sounds.

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