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Determining the Effective Features in Classification of Heart Sounds Using Trained Intelligent Network and Genetic Algorithm

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Abstract

A power system is a nonlinear one. When turbulence occurs in the power system, the stability of the system depends on the initial operating conditions and the nature of the turbulence. Nowadays renewable energy sources including photovoltaic have a key role to meet high demand of modern societies and to maintain voltage of the buses, while they also provide clean electrical energy. However, increasing the penetration level of photovoltaic systems will affect the power grid behavior. Hence, it is necessary to analyze the impact of their penetration level on the voltage stability, reliability and design of the grid, as well as the economic aspects. Investigating the voltage stability of the buses is significant in order to determine whether the amount of photovoltaic systems penetrations are enough to maintain the voltage of the bus and also to find the perfect and most beneficial location for these system in the power grid, which is discussed in this paper. In addition, a standard 30-bus test system stimulated by ETAP software, in order to evaluate the impact of Photovoltaic system penetration level on improving voltage stability.

Keywords: Voltage stability; Penetration level; Large-scale photovoltaic systems

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1. Introduction

Listening to the heart sounds is usually used for studying heart's performance and normal and abnormal states. Heart sounds are usually heard through stethoscope and depend on the person's sensibility and experience. Heart sounds signals record heart's vibrations and blood circulation, from which the performance of heart valves and hemodynamics could be found. A healthy heart's sound signal consists of s1 and s2. In cases where there is heart abnormality, multiple other signals also could occur between first and second heart sounds and might indicate heart abnormality.

Murmur is one of the heart abnormalities which presence in the heart sounds as a symptom of a problem with the heart valves. Murmur sound is like turbulent fluid that occurred between s1 and s2 or between s2 and next s1 which can represent many cardiac abnormalities [1]. Another heart abnormality is extra sounds available in heart sounds. Since extra sounds available in heart sounds might also indicate a disease, its primary and early diagnosis could be helpful for the patient. Due to the importance of early diagnosis for cardiac disease, a lot of people are looking to find a good solution for diagnosis using different mathematical and software solutions.

Most papers, regardless of their data collection method, perform feature extraction and classification for classifying partitioned heart sounds. Extracted features are fed to artificial neural networks like ANN , MLP , SVM, HMMs and GAL by which anomaly and abnormality of heart sounds are investigated. In the thresholding idea for diagnosis of s1 and s2 waves, continuous wavelet transform and iterative hierarchical methods have been used for detection and classification respectively, positive prognosis rate and sensitivity are obtained 0.95 and 0.63 respectively. [2]

In diagnosing aortic stenosis from analyzing heart sounds signals, and detecting healthy and people with mild and severe aortic stenosis, heart sound interval has been divided to 12 parts and wavelet transform spectrum, Fourier transform, power spectrum, energy changes over time, Shannon energy and entropy have been evaluated as consistent features, and sensitivity of all three classes of 88.6, 94.7,and 68.8 have been extracted respectively. [3]. In classification of heart sounds using homomorphic filtering and the k-means classifier in order to detect normal sound, systolic and diastolic murmurs from discrete wavelet transform, second heart sound, peak intensity, peak quantity and cardiac cycle have been used in order to derive features, and classification rates of 97.01, 97.01 and 95.55 have been reported. [4] Shannon entropy and energy have been used to detect normal sound, murmur and extra sounds, turbulences in the digital scope and i scope as features, and these have been combined using a method named the absorption mapping method, and the classification precision has been calculated to be 3.17, 2.03. [5]

EMD (Empirical Mode Decomposition) iterative method alongside zero crossing, symmetric covariance and finding local extremums have been used for feature derivation and the accuracy has been calculated to be 67.7, 84.21 and 80.95 in three classes of systolic and diastolic murmurs and natural heart sound. [6] In classification of natural and unnatural heart sounds, features like total systolic power, systolic Q factor, S1 interval time, the time between the end of S1 and the beginning of S2 and Mean12 have been chosen without using ECG-gating and from Cepstral, time frequency features, the classification has been done and the accuracy has been calculated to be 93.3.[7] In classification of natural sounds, murmur, extra sounds and turbulences in the i-scope with Cepstral features, like MFCC and LPC (Linear Predictive Coding) and zero crossing have been used, and the classification rate has been calculated to be 98.87. [8] Nonlinear dynamics of the correlation dimension and Lyapunov exponent have been used to study the Cepstral features of human voice together with nonlinear features, and the classification rate has been obtained as 96.67. [9] Summary of the previous work has been shown in table 1. In this research, the aim is to find the best feature from time, frequency, Cepstral, time-scale and chaotic features using the UTA feature selection method or the genetic algorithm as well [10] to classify the existing heart sounds in the Pascal challenge data [1].

Table.1.
A summary of the previous works' results

Reference Number	***The executed classification***	***Database***	***Extracted Feature Types***	***Reported parameter***	***Result***
2	Detecting S1 and S2 waves	PASCAL challenge	Shannon energy and entropy; Continuous wavelet transform	Positive prognosis rate and sensitivity	0.91 0.95-0.97 0.63
3	Detecting healthy people and people with mild and severe aortic stenosis	Recorded by the person him/herself	Dividing the heart sound to 12 parts Deriving Shannon energy and entropy's power in each part and finding their ratio compared to each other	All three general specificity classes' sensitivity and classification accuracy	94.7 68.8 85.4 88.6
4	Detecting natural sound, murmur in the first half and murmur in the second half	Recorded by the person him/herself	Heart sound's second interval, Shannon energy and entropy's peak intensity from wavelet transform	Classification rate	97.01 97.01 95.55
5	Detecting natural sounds, murmurs, extra sounds and turbulences in digital scope and I	PASCAL challenge	Shannon energy and entropy's discrete wavelet transform and combining using absorption point	Classification accuracy	3.17 2.03
6	Detecting S1 and S2 waves and murmur in the first and second halves	Recorded by the person him/herself	Zero crossing, local extremums, standard deviation and EMD iterative method	Accuracy in three classes	67.7 84.21 80.95
7	Detecting natural sound, murmur	PASCAL challenge digital section	First half's total power, first half's q factor, S1 interval time, the time between the end of S1 and the beginning of S2 and mean12	Accuracy	93.3
8	Detecting natural sound, murmur and extra sounds and turbulences in i-scope	PASCAL challenge I section	Zero crossing, cepstral and Mel frequency features, frequency power	Classification rate	98.87
9	Detecting and removing human voice anomalies	Recorded by the person him/herself	Correlation dimension and Lyapunov exponent's coefficients	Classification rate	94.69 87.35 96.67

2. Method

First, the data are normalized according to Equation 1, then different features are extracted and after that they're classified, the effective features are selected and reclassified using two feature selection methods.

$$tfi(:,1:37) = tfi(:,1:37)/\max(abs(tfi(:,1:37))) \quad (1)$$

Where tfi is the matrix involving all of the selected features. Figure 1 is shown the method process.

3. Feature Extraction

A) Time features

The main signal's zero crossing [7, 8] has been extracted from mean and maximum temporal features of the values of systolic peak, diastolic peak and main signal's peak [7]. The signal is divided to three main signal parts, namely all of the recordings, data's first half and data's second half, and then the peaks of the first part, second part and main signal have been extracted. In order to find the peak, a vector consisting of the local extremums is extracted from the input signal and the highest value is used as the peak. The local maximum is a data which its value is higher than its neighbors. If the signal is uniform, the lowest feature value would be the indicator. Also, this code shows peak locations. In order to determine main signal's zero crossing, just one of the crossings from positive to negative or vice versa according to the sample value which shouldn't be a noise could be considered. It is assumed that both positive and negative zero crossings have been calculated. In this method the zero crossing's location is calculated by drawing a linear approximation.

B) Time-Scale Features

In the wavelet transform algorithm, first the input signal is divided by half, where the first level's approximation and details are extracted from the downward and upward filters respectively. In the next step the first level's approximation are divided to approximation and details. Shannon energy is extracted from both approximation and details of the wavelet [5]. Normalized Shannon energy is calculated using equations 2 and 3, where s is the main signal, "si" are coefficients of "s" based on the varnoual.

$$E1(s_i) = s_i^2 \log(s_i^2) \quad (2)$$

$$E(s) = -\sum_i s_i^2 \log(s_i^2) \quad (3)$$

Approximations' total power has been calculated as well. In order to calculate total power, the signal is multiplied by its own convolution and divided by its own length. Wavelet transform approximations' first half mean and maximum values, second half approximations' peak transformation approximation and main signal's approximations peak are extracted according to the local maximums algorithm [7]. Each discretization level's generalities and details extracted energy and the details absolute value have been extracted.

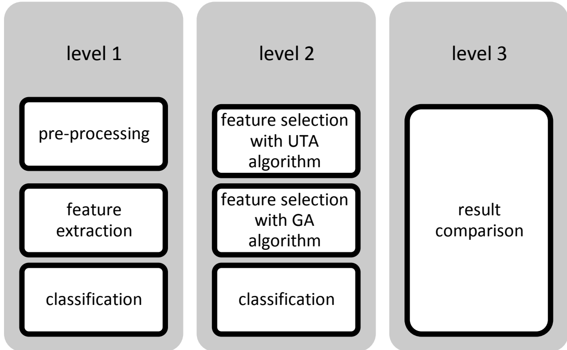

Fig. 1. method process

C) Frequency Features

Frequency features like main signal's bandwidth, first half's bandwidth [7] and second half's bandwidth are also extracted. Signal frequency bandwidth has also been extracted from the Fourier transform.

D) Cepstral Features

Among Cepstral features, the Mel frequency feature has been extracted. Cepstral coefficients which are obtained from the signal's inverse Fourier transform logarithm give 13 features [8]. Also, the data's standard deviation and Cepstral features' peak have been extracted.

E) Non-linear and chaotic features

Lyapunov exponents are dynamic features indicating the separation rate of the paths extremely close to zero, and they're equal to the phase dimensions. Lyapunov exponents' maximum is usually extracted to make the dynamic system predictable, where if the obtained coefficient is larger than one, it indicates that the signal is turbulent [9]. All of the features extracted in the present study are noted in Table 2.

4. Classification

Three-layer perceptron classifier has been used for classification in the early stages of the work. Training and testing data have been randomly changed in order to find the accuracy of the classification. To avoid extra training the network for the data with higher number of samples compared to others, 70 percent of the smallest data has been considered for classification of the training and testing group.

5. Effective Features Selection

A) UTA Method

UTA is one of the fast and effective methods for selecting the effective features based on the trained intelligent network [10]. In this method, first the network is needed to be trained by every feature which has been done in the previous stage alongside finding the accuracy of each class. Then, one feature's mean is replaced for every example in each algorithm iteration, and the network is tested with this new feature. In this study, accuracy difference is considered as a criterion for the effectiveness of one feature. The increase or consistency of accuracy for a feature means that it is harmful or non-effective and could be neglected. If that feature's accuracy value decreases, it is considered as being effective.

After performing the stages above for every feature, effective features have been selected as optimal subsets. Then the network has been trained and tested using these new features and the accuracy percentage is calculated, where same initial results or even better ones are expected to be obtained [10].

It was found in the available investigations in this project that every signal recorded by the digital stethoscope had a turbulent state due to high Lyapunov exponents, but since non-effectiveness of these features in the classification of the signals recorded using digital stethoscope was found after being tested in UTA, its calculation for the signals recorded using the i-stethoscope was skipped. The selection features using the UTA method have been noted for both types of scopes in tables 3 and 4.

B) Feature Selection Using Genetic Algorithm

The genetic algorithm could be considered as a general searching method which imitates the laws of natural biological evolution [12]. According to the law of natural selection, the only species surviving in a population are the ones with the best features.

The fundamental idea of this algorithm is genetic transmission of hereditary characteristics. The set of human characteristics is transmitted to the next generation by chromosomes. Each gene features on characteristic. In fact two things happen simultaneously for chromosomes. On is the mixture of one chromosome with another. The other is mutation so that some genes in the chromosome change randomly.

- Genetic algorithm flowchart:
- The algorithm begins with a population of n chromosomes with eandom ingredients.
- Fitness is calculated for each person
- Two people are chosen based on higher fitness
- Mixing and the birth of children from parents
- Applying mutation with a probability of p for each child
- Putting the born-children as the new generation
- End of the algorithm

In this method, feature selection is demonstrated using binary strings as ones and zeros, where one indicates the presence of that feature while zero indicates the absence of the feature. Each of these strings are called a chromosome and their suitability is evaluated by their fitness [11]. The selected features using the genetic algorithm method for both types of scope are noted in tables 5 and 6.

6. Results

In this paper, PASCAL challenge [1] data have been used where 124 sounds have been recorded by i-stethoscope and 287 have been recorded by the digital stethoscope. The data recorded by the i-stethoscope involve 4 parts: natural, murmur, extra sounds and turbulences, each of which has 31, 34, 18 and 14 samples respectively. The data recorded by the digital stethoscope involve 3 parts: natural, murmur and extra sounds in the systole, each of which has 120, 66 and 46 samples respectively. Daubechies 6 wavelet transform with 4 discretization levels has been used to derive time-scale features. In the classification for the i-stethoscope, the number of neurons is considered to be 7 for the first hidden layer and 5 for the second hidden layer. This is while for the digital stethoscope, the number of neurons is considered to be 10 for the first hidden layer and 15 for the second hidden layer. In this study, a decrease of more than 3% in accuracy has been considered as the feature effect on the data recorded by the i-stethoscope to remove the non-effective, harmful features in the UTA method. Also, a decrease of more than 5% in accuracy has been considered as the feature effect on the data recorded by the digital stethoscope to remove the non-effective, harmful features. Also, K-means clustering algorithm has been used for feature selection in the genetic algorithm.

Here, the initial population, the number of generations and the population type have been considered to be 30, 30 and binary respectively. Competitive method has been used for selection, where each parent randomly selects the best person of the group as a parent according to the competition rate. The competition rate is considered to be 2.

Uniform mutation which is a 2-stage process has been used for the mutation. First, the segmentation algorithm selects one person from the input vector for the mutation, where each input has the probability of mutation which its rate here is considered to be 0.1. In the second stage, each selected input is randomly and uniformly replaced by the random number.

Mathematical mixing has been used for mixture, where children are created with their weight being the mean of their parents' weights. The rate here is considered to be 0.8 .Parameters like sensitivity, specificity and accuracy have been used for checking the results, each of which is calculated using equations 2, 3 and 4 respectively. All of the classification results including classification with all features, features selected by the UTA method and features selected by the digital stethoscope have been noted in tables 7, 8, 9, 10 and 11.

$$Se = \frac{TP}{TP + FN} \quad (4)$$

$$Sp = \frac{TN}{TN + FP} \quad (5)$$

$$ACC = \frac{TP + TN}{TP + FN + TN + FP} \quad (6)$$

7. Discussion

According to the results, it's seen that when selecting the features using the UTA algorithm, a 4.25% increase has occurred on average in the classification accuracy for the i-stethoscope. Also, in the genetic algorithm, approximately 0.75% increase has occurred on average in the classification accuracy by selecting only 7 features. And despite reducing the features there are no changes in the classification accuracy on average for the digital stethoscope. Therefore one of the research objectives which was determining the most effective features has been accomplished. Another objective for this study was reducing the number of false positives and false negatives, yet it's observed that in some classes the false positives and negatives total is still significant.

Table.2.
Extracted feature

Item	Extracted feature list
1	Wavelet transform generalities' Shannon energy
2	Wavelet transform details' Shannon energy
3	Wavelet transform generalities' power
4	Wavelet transform generalities' peak maximum
5	Wavelet transform generalities first half's peak maximum
6	Wavelet transform generalities second half's peak max.
7	Wavelet transform generalities' energy
8	Wavelet transform 1st level details' energy
9	Wavelet transform 2nd level details' energy
10	Wavelet transform 3rd level details' energy
11	Wavelet transform 4th level details' energy
12	Wavelet transform generalities' absolute value
13	13 features of Mel frequency
14	Mel frequency feature's standard deviation
15	Mel frequency feature's maximum
16	Signal's zero crossing
17	Main signal's peak maximum
18	Main signal's peak mean
19	First half's peak maximum
20	First half's peak mean
21	Second half's peak
22	Main signal's bandwidth
23	First half's bandwidth
24	Second half's bandwidth
25	Frequency spectrum's power
26	Lyapunov exponent

Table.3.
Extracted feature with UTA method for i stethoscope

Item	*Extracted feature list*
1	Wavelet transform generalities' second half maximum
2	Wavelet transform generalities' energy
3	Wavelet transform 4th level detail's energy
4	10 features of Mel frequency (one, three, four, five, six, seven, eight, ten, eleven, twelve)
5	Mel frequency feature's standard deviation
6	Mel frequency feature's peak maximum
7	Signal's zero crossing
8	Main signal's peak maximum
9	First half's peak maximum

Table.4.
Extracted feature with UTA method for digital stethoscope

Item	*Extracted feature list*
1	Wavelet transform generalities' peak maximum
2	Wavelet transform generalities second half's peak maximum
3	Wavelet transform 2nd level detail's energy
4	Wavelet transform 4th level details' energy
5	10 features of Mel frequency (1,3,4,5,7,8,9,10,12,13)
6	Mel frequency feature's standard deviation
7	Mel frequency feature's maximum
8	Main signal's peak maximum
9	Main signal's peak mean
10	First half's peak maximum
11	First half's peak mean
12	Second half's peak
13	Main signal's bandwidth
14	First half's bandwidth
15	Second half's bandwidth
16	Frequency spectrum's power

Table.5.
Extracted feature with genetic algorithm method for i stethoscope

Item	*Extracted feature list*
1	6 features of Mel frequency (3,4,5,6,12,13)
2	Main signal's bandwidth

Table.6.
Extracted feature with genetic algorithm method for digital stethoscope

Item	*Extracted feature list*
1	Wavelet transform generalities' diastolic peak maximum
2	Wavelet transform 2nd level details' energy
3	6 features of Mel frequency (six, eight, ten, eleven, twelve, thirteen)
4	Main signal's bandwidth

Table.7.
Primary classification with all the features for i stethoscope with 10 times selection test and train data

Level	*Sensitivity*	*Specificity*	*Accuracy*	*FP+FN*
Artifact	85	93	90	6
Extrasound	80	91	90	6
Murmur	81	93	89	7
Normal	47	98	85	10

Table.8.
Primary classification with all the features for digital stethoscope with 10 times selection test and train data

Level	*Sensitivity*	*Specificity*	*Accuracy*	*FP+FN*
Extrasound	84	69	70	50
Murmur	74	86	83	23
Normal	56	96	65	63

Table.9.
Classification with selected features by UTA method for i stethoscope with 10 times selection test and train data

Level	*Sensitivity*	*Specificity*	*Accuracy*	*FP+FN*
Artifact	87	97	93	5
Extrasound	92	96	96	3
Murmur	85	94	91	6
Normal	68	99	91	6

Table.10.
Classification with selected features by UTA method for digital stethoscope with 10 times selection test and train data

Level	*Sensitivity*	*Specificity*	*Accuracy*	*FP+FN*
Extrasound	91	68	70	51
Murmur	77	85	83	23
Normal	54	98	64	65

Table.11.
Classification with selected features by genetic algorithm method for i stethoscope with 10 times selection test and train data

Level	*Sensitivity*	*Specificity*	*Accuracy*	*FP+FN*
Artifact	75	97	87	8
Extrasound	97	92	92	5
Murmur	76	96	89	7
Normal	63	97	89	7

Table.12.
Classification with selected features by genetic algorithm method for digital stethoscope with 10 times selection test and train data

Level	*Sensitivity*	*Specificity*	*Accuracy*	*FP+FN*
Extrasound	72	68	68	51
Murmur	76	79	78	30
Normal	52	97	61	69

8. Future Working

According to the obtained results, it is suggested that the following are studied in future research:

- Deriving the selected features from capstral coefficients using other feature-selection methods
- Implementing this method on medical algorithms in order to reduce human error

Reference

[1] P. Bentley, G. Nordehn, M. Coimbra, and S. Mannor, "The PASCAL Classifying Heart Sounds Challenge Results", CHSC2011

[2] N. Marques, R. Almeida, A. P. Rocha, M. Coimbra, "Exploring the Stationary Wavelet Transform Detail Coefficients for Detection and Identification of the S1 and S2 Heart Sounds", IEEE 14033708, 2016.

[3] A. Voss, A. Mix, R. Schroeder, Thomas," Diagnosing aortic valve stenosis by parameter extraction of heart sound signals", 2007

[4] N. Cota, S. Sundaram, M. Shankar, " Neural network classification of homomorphic segmented heart sounds",2005.

[5] Shi. Deng, Ji.Qing,"Towards heart sound classification without segmentation via autocorrelation feature and diffusion maps", 2016.

[6] A. Shelke, V.B. Baru Sinhgad, "Heart Valve Disease Classification Using Neural Network", International Journal of Science and Research, IJSR, 2017.

[7] M. Singh, A. Cheema," Heart Sounds Classification using Feature Extraction of Phonocardiography Signal", International Journal of Computer Applications, 2013.

[8] S. Ali, S. M. Adnan, T. Nawaz, M. Obaid Ullah, S. Aziz. "Human Heart Sounds Classification using Ensemble Method", 2017.

[9] G Vaziri, F Almas Ganj, "Evaluation and Diagnosis of Voice Abnormalities using Chaotic Feature ", 2008.

[10] M.Shkohi Fard,"Selection Features Methods Comparison of the Classic Methods of Evolution Optimization Algorithm",2008.