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COVID-19 Diagnosis Using Spectral and Statistical Analysis of Cough Recordings Based on the Combination of SVD and DWT

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Abstract:

Healthcare professionals routinely use audio signals, generated by the human body, to help diagnose disease or assess its progression. With new technologies, it is now possible to collect human-generated sounds, such as coughing. Audio-based machine learning technologies can be adopted for automatic analysis of collected data. Valuable and rich information can be obtained from the cough signal and extracting effective characteristics from a finite duration time interval that changes as a function of time. This article presents a proposed approach to the detection and diagnosis of COVID-19 through the processing of cough collected from patients suffering from the most common symptoms of this pandemic. The proposed method is based on adopting a combination of Singular Value Decomposition (SVD), and Discrete Wavelet Transform (DWT). The combination of these two signal processing techniques is gaining lots of interest in the field of speaker and speech recognition. As a cough recognition approach, we found it well-performing, as it generates and utilizes an efficient minimum number of features. Mean and median frequencies, which are known to be the most useful features in the frequency domain, are applied to generate an effective statistical measure to compare the results. The hybrid structure of DWT and SVD, adopted in this approach adds to its efficiency, where a 200 times reduction, in terms of the number of operations, is achieved. Despite the fact that symptoms of the infected and non-infected people used in the study are having lots of similarities, diagnosis results obtained from the application of the proposed approach show high diagnosis rate, which is proved through the matching with relevant PCR tests. The proposed approach is open for more improvements with its performance further assured by enlarging the dataset, while including healthy people.

Keywords: Corona Virus, Cough Sound, COVID-19, DWT, Feature Extraction, Signal Processing, Statistical Analysis, SVD.

Introduction:

Coronavirus disease (COVID-19) is an infectious illness caused by a newly discovered coronavirus. This disease is attributed to Severe Acute Respiratory Syndrome Corona-Virus 2 (SARS-CoV_2), which is categorized as an RNA virus and widely distributed in humans and other mammals.

The first documented human infection of COVID-19 was reported in Wuhan City, in China, in December, 2019, then later in many parts within the world. At March 11th, 2020, the World Health Organization (WHO) characterized the continuous outbreak as a pandemic[1].

Transmission may occur either directly during patient coughing, sneezing or talking, via infected droplets or indirectly by touching surfaces or objects contaminated by the infected patients[2].
Signs and symptoms of the (COVID-19) disease can appear after two to 14 days following exposure. The period between exposure to the appearance of symptoms is known as the incubation period[3].
Cough, a dry type, is a commonly seen as a primary symptom of COVID-19, particularly in the early course of the complaint, and it is recorded in nearly 70% of cases who were symptomatic. It is a common symptom in the acute stage of the infection, and it may stay till the recovery stage. Coughing is not only annoying to patients, but also raises the risk of infections via respiratory droplets. Other features of COVID-19 are pyrexia, losing of smell, losing of taste, fatigability, and anorexia[4,5].

Because the cough stimulus is mediated by the vagus nerve, so interactions between the airways vagus innervation and the virus, with resulting neuro-inflammatory reply, represents the likely major steps for the beginning of cough[5].

Cough is a reflex which requires minimal conscious control, occurring through stimulation of sensory peripheral nerves into the vagus nerves. In cough that is long lasting (chronic), the phrase of cough hypersensitivity has been broadly used keeping in mind that the cough triggers have been activated by amplification of those afferent impulses up to the brainstem. Therefore, it is well known that neuronal mechanisms of hyper-sensitivity are essential to the cough of COVID-19. With the note that SARS-CoV_2 targets the sensory nerves stimulating cough, resulting in neuro-inflammatory and neuro-immunological interactions as mechanisms of cough hypersensitivity[6].
A dominant, and sometimes the only observable, symptom in most lung illnesses including airway diseases such as pneumonia and tuberculosis, is known to be the cough. Cough sounds can be helpful and influential in the diagnosis of certain diseases. The main characteristics of cough such as intensity and frequency may also infer the intensity of a specific illness, making cough a useful tool in the diagnosis of certain medical conditions.

To use the cough in illness diagnosis, it is needed to identify the audio features of interest in analyzing the cough event. Audio features within the acoustic signal are used to verify the occurrence of a cough event and to describe the nature of the cough. Among these features are the mean and median frequencies, which are known to be operative and useful features in the frequency domain. They are, therefore, applied in the approach proposed in our paper to generate an effective statistical measure to compare the results. The proposed approach of detecting and diagnosing COVID-19 is based on processing and analyzing cough sounds being collected from patients suffering from the most common symptoms of this pandemic. The proposed method adopts a combination of Singular Value Decomposition (SVD), and Discrete Wavelet Transform (DWT). The use of the two signal processing techniques has led to a well-performing cough recognition approach, where it produces and utilizes an efficient minimum number of features.

For a given data sample that is to be processed and analyzed, the application of our proposed approach is distinguished by about 200 times reduction, in terms of the number of operations, which is a considerable performance efficiency. Together with this achievement, we intend to reach to a high diagnosis of COVID-19 infection through cough recognition.

The paper is organized as follows; after the introduction presented in this section, the related work and literature is presented in the next section. Description of the proposed approach of COVID-19 detection and diagnosis based on cough analysis, is found in the third section. Section four is dedicated for the results and their analysis, where the collected data, categorized based on age groups, is processed and investigated. Values of the mean and median frequency estimation measures, applied to the outputs of SVD and DWT for 40 adopted cases, are tabulated and presented. The discussion of results is included in the fifth section. In the discussion part an emphasis and focus are given to explain the behavior of the results with respect to the adopted cases, as well as the evaluation of the performance of the proposed approach. Conclusions are in the last section of the paper.

Related Work:

An audio signal is known to be a decomposition of three parts; namely, voiced, unvoiced, and silent parts. The high-amplitude and low-frequency components are contained in the voiced part, while the unvoiced part contains the low-amplitude and high-frequency signals. In the silent part, however, components with frequencies and amplitudes, that are of no significance, are contained[7]. There are many applications in mathematics, computer science, engineering and science for signal transform techniques, such as; Discrete Wavelet Transform (DWT), Discrete Cosine Transform (DCT), and Singular Value Decomposition (SVD)[8]. Singular Value Decomposition (SVD); for instance, has been used in image coding, and signal enhancement.

A book chapter authored by Zehtabian *et al.*, dealt with speech enhancement approaches based on an optimized Singular Vector denoising schema [9]. The adopted SVD approach, which is basically relying on the generalization of the Eigen decomposition of a positive semi definite normal matrix via an extension of the polar decomposition, is efficient in enhancing the noisy signal by retaining few of the singular values from the decomposition of an over determined, over-extended data matrix. An investigation study was performed by Kour *et al.* on the effect of SVD based feature selection of the input speech on the perception of the processed speech signal, where speech of six speakers was recorded and the English language vowels were analyzed using SVD based processing[10].

As digital images require large amount of memory, and due to the large data associated with them, the SVD approach was also use by Compton and Ernstberger to manipulate the large sets of data, through the removal of the singular values to reduce the size of stored images, and by identifying the components of the image contributing the least to overall image quality[11].

More published literature related to the application of SVD, DWT and DCT in signal and image processing applications is also available [12-14]. Applications on text, audio and video processing applications that are mainly adopting techniques in spatial domain and frequency domain have been considered for investigation. Watermarking methods based on DWT-SVD and RDWT-SVD and signal steganography are among the more adopted areas by researchers. Kanhe *et al.* authored two relevant works [15,16]. A speech steganography method is presented, where a Discrete Cosine Transform (DCT) is cascaded with singular value decomposition (SVD). In this method, an increased imperceptibility of the steganography is achieved by embedding the message by only using voiced frames[15]. Meanwhile, a method based on DCT used both voiced and un-voiced characteristics for audio steganography. Although the method is based on the fact that the amplitude of the DCT coefficients is changed by message bits, the changes are found different for the voiced and unvoiced parts of the audio signal[16].

In addition to their application in digital watermarking, the combined DWT and SVD are used in ECG signal and the human speech processing. For example, the three signal transforms (DWT, SVD, and DCT) are coupled with the compressive sensing (CS) theory to generate hybrid measurements. In this work, Rohit Thanki, *et al.* presented a method by which they analyzed and tested various signals such as ECG and the human speech signals[17]. Guarding the digital content of owners in the digital watermark system was considered by another paper presented by Yuhui Li, *et al*, ***where*** a technique based on the adoption of SVD and DWT, was proposed attributing to the performance of the algorithmic steps for digital watermarking. The proposed method is claimed to be robust against various added noise, cropping, zoom, rotating, and compression and filtering[18]. In the work presented by Mohammed e*t al.*, a review of many research works that are adopting the (DWT, SVD and DCT) signal transforms, is analyzed and presented[19]. In the image encoding area, the combination of Discrete Wavelet Transform (DWT), and Discrete Cosine Transform (DCT) together with the Sliding Run Length Encoding (SRLE) technique are adopted to get an improved image compression[20].

The digital watermarking algorithms and multimedia security, which are based on DWT and SVD techniques, have been the focal point of considerable researches activity because of their wide application area.

In a recent work, Abdelwahab *et al*., presented a cancelable speaker identification system based on a hybrid structure of DWT and SVD, where a watermarking algorithm is implemented to control the level of intended distortion in a speech signal before the identification process[21].

Another new publication, was proposed by Kumar, and Kanhe, where a secured speech watermarking with DCT compression and chaotic embedding using DWT and SVD, is presented[22]. Authors of this work claimed that their proposed algorithm can resist to various signal processing attacks such as noise addition, low-pass filtering, requantization, resampling, amplitude scaling, and MP3 compression.

Two techniques were adopted to achieve more protection and resistance against some attacks such as JPEG compression, scaling and filtering, the scheme performed well against the remaining attacks. The results also show high efficiency and robustness in handling image watermarking using these techniques. This proposed algorithm can be considered as robust against ‘filtering’, which represents compression-based attacks, and `scaling' and `rotation', which signify geometric attacks[23,24].

The detection of voice disorders issues was considered by some research works. In a paper by Everthon Silva Fonsecaa *et al.*, the concepts of signal energy (SE), zero-crossing rates (ZCRs) and signal entropy (SE), were used to provide a joint time-frequency-information map that achieved a result for groundbreaking accuracy of 95% and classifies voice signals on the basis of discriminative paraconsistent machine (DPM) application of paraconsistency method to treat voice definitions and contradictions[25]. In the paper presented by Rimah Amami *et al.*, the methodology was to use Incremental DBSCAN-SVM, Support Vector Machines (SVM) classifier with Radial Basis Function (RBF) Kernel applications for voice pathology detection, and the results showed a great accuracy of 98%[26]. Ghulam Muhammada *et al.* work demonstrated the vocal tract irregularity features and support vector machine classifier application on two datasets; MEEI and SVD databases, resulting in 99.22% and 94.7% accuracy respectively[27]. Manasi Bendale *et al.* presented disease identification system that differentiates clinical conditions associated with unnatural voice and methodologies that are adopted for assessing characteristic varieties in voice of people. The paper confirms the accomplishment of the voice investigation frameworks and brings up normal ailments that sway understanding voice patterns for driving research that have affirmed voice modifications as demonstrative manifestations in their respective ailments and also the technique by which voice analysis can be done[28].

A dominant, and sometimes the only observable, symptom in most lung illnesses including airway diseases such as pneumonia and tuberculosis, is known to be the cough[29]. Cough sounds, as an observable symptom in most lung illnesses, are used in the diagnosis, where they have been found helpful and of influenceable. The main characteristics of cough such as intensity and frequency may be an evident feature adding to the intensity of a specific illness, making cough a useful tool in the diagnosis of certain medical conditions[30].

To use the cough in illness diagnosis, the audio features of interest in analyzing the cough event need to be identified. Audio features within the acoustic signal are broadly categorized as temporal and spectral. They are used to verify the occurrence of a cough event and to describe the nature of the cough.

One such important feature is the energy distribution in the spectrogram, and the analysis of energy components in the cough signals was used for the purpose of COVID-19 detection and diagnosis[31].

Salah and Ahmed proposed a decision support system to help within the medical care, specifically to control the Corona Virus Disease (COVID-19) virus pandemic. The system aims to determine the class of infection and to provide a suitable protocol treatment depending on the symptoms of a patient. Diagnosis of COVID-19 relies mainly on the detection of the main symptoms (fever, tiredness, dry cough and breathing difficulty). Infected people are then divided up into four classes, based on their immune system risk level. The system is further proposed two indices of age and current health status, where people are graded and expected to comply with their class regulations[32].

Renard *et al.* proposed an algorithm which is based on analyzing cough and whoop sounds for diagnosis of pertussis. The algorithm performs its operation through extracting relevant features from the audio signal by adopting three main steps; cough detection, cough classification, and whooping sound detection. Authors of this work have evaluated the performance of their proposed algorithm by using audio recordings from 38 patients[33].

Zealouk *et al*., adopted the Hidden Markov Model (HMM) speech recognition classification, formants frequency and pitch analysis to study the cough changes of COVID-19 infected and healthy people[34]. Their system is implemented with 5 HMM states, 8 Gaussian Mixture Distributions (GMMs) with 39 dimensions of the overall feature vector. Results presented the difference between the recognition rates of infected and non-infected people is 6.7%. Whereas, the formant analysis variation based on the cough of infected and non-infected people is clearly observed with F1, F3 and F4, while F0 and F2 are lower[34].

A method based on analyzing coughs and breathing to understand how perceptible COVID-19 sounds are from those in asthma or healthy controls is published. It is stated that this work has succeeded to classify correctly healthy and COVID-19 sounds by adopting simple machine learning classifier. Results of this recent research showed that it is possible to distinguish individual cases that tested positive for COVID-19 and had a cough from a healthy case with a cough, and who tested positive for COVID-19 and had a cough from that one with asthma and a cough[35]. A robust method of informative under sampling using information rate to deal with the imbalance is introduced. The work investigates the use of symbolic recurrence quantification measures for the automatic detection of COVID-19 in cough sounds of healthy and sick individuals. The results of the proposed model performance, for coughs and sustained vowels, respectively reached a mean classification of 97% and 99%, and a mean *F*1-score of 91% and 89% after optimization[36].

There are several researches dealing with the discovery and discrimination of the Corona virus, and most of them focus on the medical aspect, particularly some of them focus on pictures of the lungs. And the biggest challenge in this research is that the samples obtained are all infected with respiratory diseases, so they are similar to the symptoms of those infected with Corona. Differentiating between them therefore, needs an effective method. For this reason, we proposed a combination of SVD and DWT in order to get an efficient cough recognition approach.

Materials and Methods:

Proposed Approach of COVID-19 Detection and Diagnosis:

The approach adopted in our paper is mainly related to the category of digital signal processing and analysis approaches. It represents an easy and effective method focusing on reducing the system complexity. The approach is featured by the capability of reaching to a considerable decrease in the number of operations involved in the processing and analysis. Following is a brief description of the six main steps of the proposed approach, which are illustrated in Fig.1.

Acquisition of Cough Signal:

This section is concerned with collecting cough signals from volunteers, who are admitted to the hospital for various medical reasons, most of which were related to the respiratory system. A microphone of a mobile phone is used to record coughs of these patients, which are then transferred into the computer for processing and analysis. Forty cough records composed of 20 normal cases, and 20 covid-19 infected cases, are taken and added as a data set.

Cough Signal Preprocessing:

The focus of this section is on preparing the cough signal for real processing. Cough signals are acquired with different lengths, so a windowing of 40000 pulses is applied for resizing them.

Cough Signal Reshaping:

As the output of preprocessing step is a vector of a size 40000 samples, so in this step, a reshaping process of size (200*200) is applied in order to reshape the signal, as a square matrix, to be adapted for the SVD process.

Applying Singular Value Decomposition (SVD):

The Singular Value Decomposition (SVD) process is applied to get a minimum of effective features that can be used for the next step of processing. Let us define the output of the reshaping process by a matrix Z(n*m), then applying SVD on this matrix can be realized as below:

$$Z_{n*m} = U_{n*n}\, S_{n*m}\, V^T_{m*m} \quad (1)$$

Where Z is an orthogonal unitary matrix of size (n*m), S is a diagonal matrix (singular value) of size (m*n) and V^T is an orthogonal (conjugate transpose) unitary matrix of size (n*n). The singular values are considered to be a square root of the eigenvalues, so, it can be realized by decomposition, rotation and stretching to reach the effective output on the diagonal matrix. In addition, the real matrix in the output of reshaping is a square matrix (m=n) of size (200*200), so there is no importance about the indexing of the square matrix. Then, storing the diagonal of the S matrix into a separated vector that represents a full rank vector of 200 values.

$$Z_n = diag(S) \quad (2)$$

Applying Discrete Wavelet Transform (DWT):

To concentrate the effective features, one-dimensional Discrete Wavelet Transform (DWT) is applied. DWT is a combination of low pass filter and high pass filter to generate a multispectral sequence. Let us consider H as an impulse response of the applied filter and the number of values at the output of SVD is 200, so DWT can be written as below:

$$y[n] = (Z * H)[n] = \sum_{k=1}^{200} Z[k]\, H[n-k] \quad (3)$$

Statistical Frequency Measures:

Both mean and median frequency measures are applied to get the important frequency features to be used for the comparison. These frequency measures are applied to the output of SVD and DWT respectively.

- **Mean Frequency (MeanF)**: Mean frequency of a cough signal is an average frequency related to the sum of the product of the signal power spectrum and the frequency then divided by the total sum of the power spectrum, as given below:

$$Mean\ Frequency = \frac{\sum_{i=0}^{N-1} F_i P_i}{\sum_{i=0}^{N-1} P_i} \quad (4)$$

Where, Fi is the frequency value of signal power spectrum at the frequency location i, P_i is the power spectrum at the frequency location i, N is the length of the frequency.

- **Median Frequency (MedF)**: Median frequency of a cough signal is a frequency at which the signal power spectrum is divided up into two parts with equal amplitude, that satisfies the following condition:

$$\sum_{i=0}^{MedF-1} P_i = \sum_{i=MedF}^{N-1} P_i = \frac{1}{2}\sum_{i=0}^{N-1} P_i \quad (5)$$

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Figure 1. Proposed approach of COVID-19 coughs recognition

Results and Discussion:

Data Collection and Analysis of Results:

The six steps of the proposed COVID-19 cough-based recognition approach are applied in order to distinguish between infected cases (those with positive test result), and noninfected cases (with negative test result). In the rest of this paper, the infected cases are referred to as abnormal, while the name normal is used to refer to noninfected COVID-19 cases.

Data Collection and Specification:

The study, presented in our paper, consists of two groups of patients, who were admitted to the epidemiology ward at Kirkuk general hospital.
Patients who are COVID-19 infected (abnormal) are confirmed by PCR testing (from nasopharyngeal and oropharyngeal swabs in Public Health Laboratory in Kirkuk, while the normal i.e., non-COVID-19 patients basically complained from other respiratory problems like asthma or chronic obstructive pulmonary disease.

Agreements of all patients were taken after informing them about the study. A mobile phone is used to record their cough sounds, where the patients are asked to take deep breath and cough through their mouths.

A set of 40 cases composed of 20 normal (non-infected) cases, and another group of 20 infected patients (abnormal) are adopted in our study. The considered cases are of mixed sex (i.e., male and female). Ages of the studied cases are also varying, where for a certain assumed case, the ages of the participants from the two COVID related groups are not exactly the same but are selected to be close and of similar age group. The division of age into groups is listed in Table 1, where a period of three years is considered for each age group.

Table 1. Age groups of the patients participated in the study

Age Group (AG)	Range (years)	Age Group (AG)	Range (years)	Age Group (AG)	Range (years)	Age Group (AG)	Range (years)
1	10-13	6	30-33	11	50-53	16	70-73
2	14-17	7	34-37	12	54-57	17	74-77
3	18-21	8	38-41	13	58-61	18	78-81
4	22-25	9	42-45	14	62-65	19	82-85
5	26-29	10	46-49	15	66-69	20	86-89

Application of the Proposed Approach:

During the application of the steps of the recognition approach, the state of the cough signal under investigation, is demonstrated in order to illustrate what happens during that process. This practice is effectively meaning that a step-by-step tracking of the cough signal starting from the beginning (i.e., when it was originally recorded using a mobile). After recording the cough signal some noise may go through the signal via many internal and external sources. Then this signal will be filtered to remove the unwanted noise that affects the quality of the signal. Fig. 2 is showing the cough signal before and after applying noise removal filter for both normal and abnormal cases.

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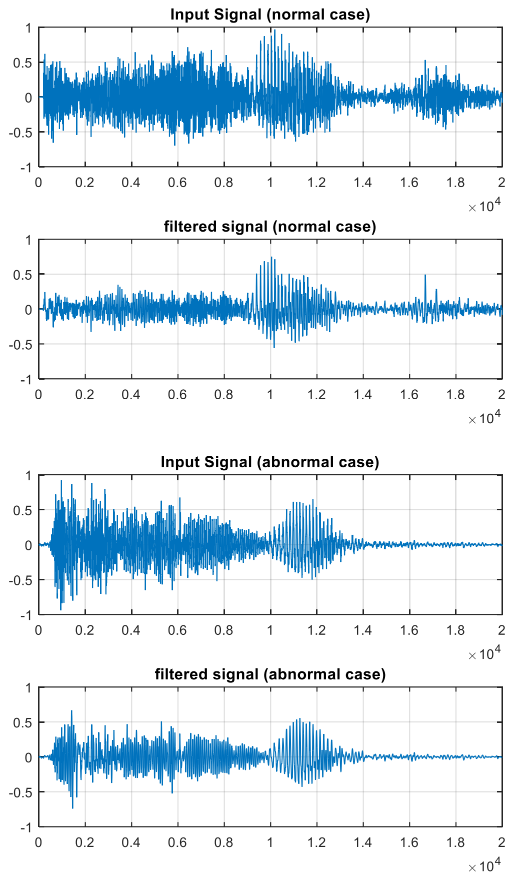

Figure 2. Input and filtered signal (normal and abnormal cases)

Signal reshape is a process that changes the shape of the data from its current position to a new one. Since the work requirement in the SVD process is to receive data in two dimensions, but the incoming cough signal is in one dimension, so, it must be changed into two-dimensional arrays. In this case, to perform the reshaping process, start converting the one-dimensional cough signal of 40000 values into two dimensional (200*200) values, which is suitable for the SVD process. The reshaping process is visualized in Fig. 3.

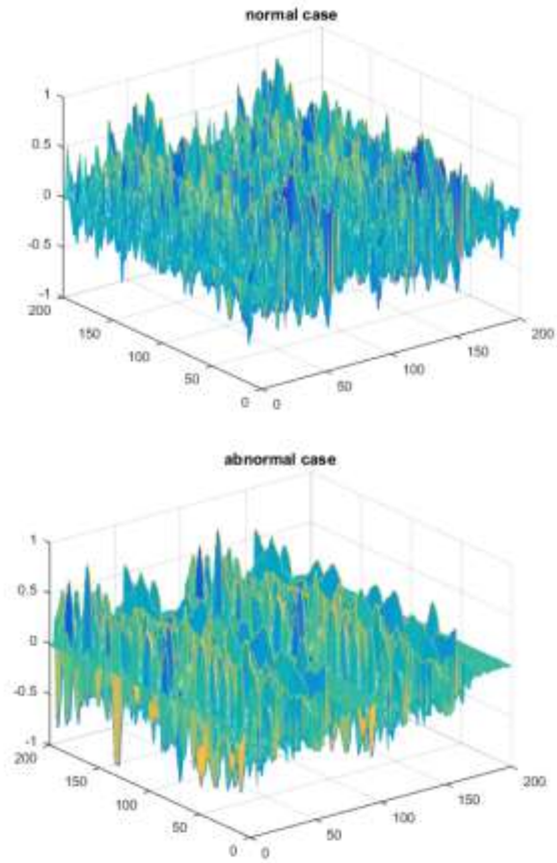

Figure 3. Reshaping of the one-dimensional cough signal (normal and abnormal)

Applying SVD of the two-dimensional cough signal will produce three matrices, one of these is a positive real diagonal matrix that has the effective features of the cough signal. Applying SVD demonstrate that just a few effective values (200 values) can be used as an input for the next step, as shown in Fig.4.

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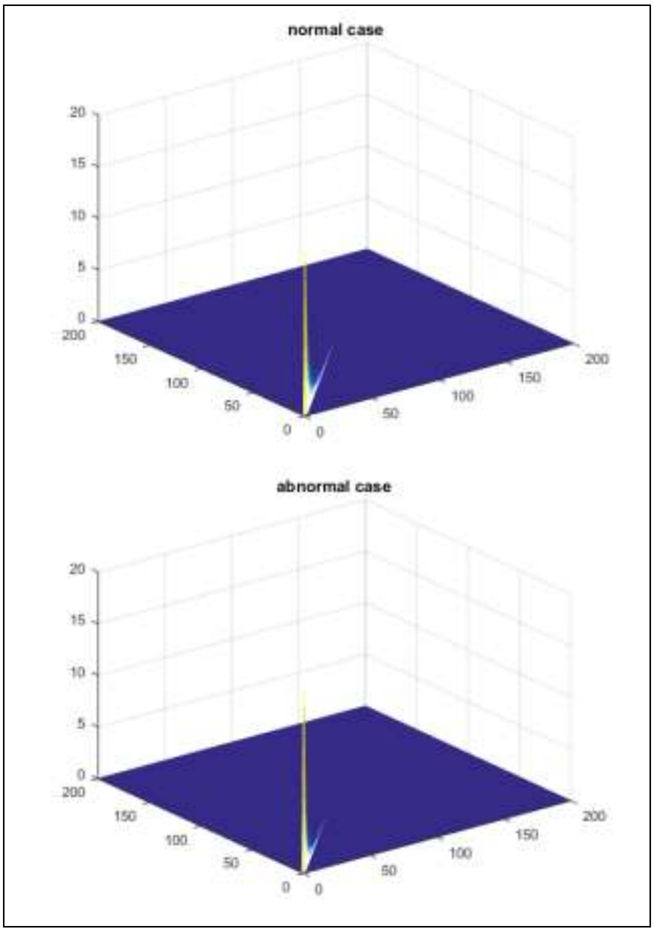

Figure 4. Applying SVD of the two-dimensional cough signal (normal and abnormal)

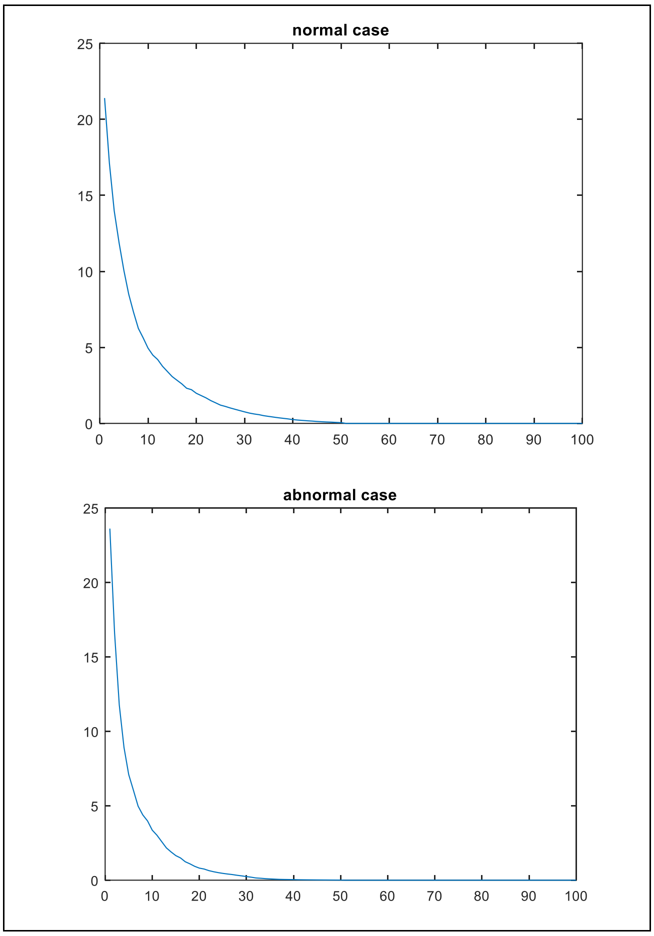

Figure 5. Applying one dimensional DWT on the output of SVD (normal and abnormal)

In Fig. 5, the curves illustrate the one-dimensional DWT applied on the output of the SVD which is the diagonal matrix of rank 200 to generate the effective features to be used for statistical measures. Applying DWT reduce the number of effective features to 100 values. It is clear from this figure, the range of the most effective features of the normal case is less than the corresponding range of the abnormal case.

Mean and median frequency estimation as statistical measures is applied after SVD and DWT to compare between normal and abnormal cases. Figure 6 demonstrate two cases (normal and abnormal) with the application of both mean and median frequency estimation for each case. Fig. 6a shows the values of mean and median frequency estimation at the output of SVD (normal case) are 1716 Hz and 551 Hz respectively, comparing with Fig. 6b with corresponding values of mean and median frequency estimation at the output of SVD (abnormal case) are 2459 Hz and 916 Hz respectively. On the other hand, Fig. 6c shows the values of mean and median frequency estimation at the output of DWT (normal case) are 2843 Hz and 1098 Hz respectively, comparing with Fig. 6d with corresponding values of mean and median frequency estimation at the output of DWT (abnormal case) are 4065 Hz and 1811 Hz respectively. This illustrates that there is a significant difference between normal and abnormal cases.

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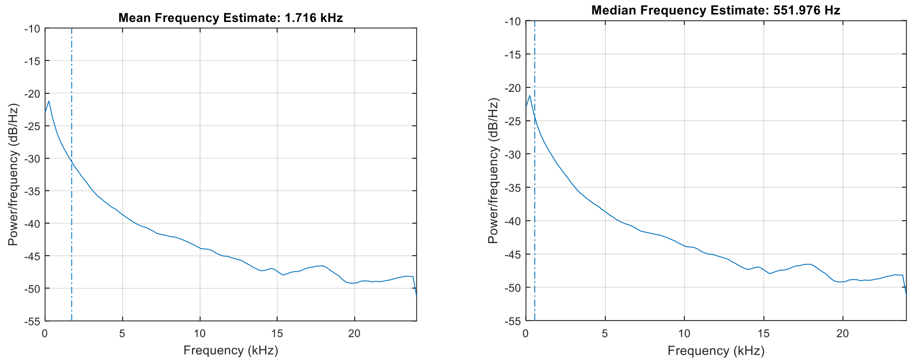
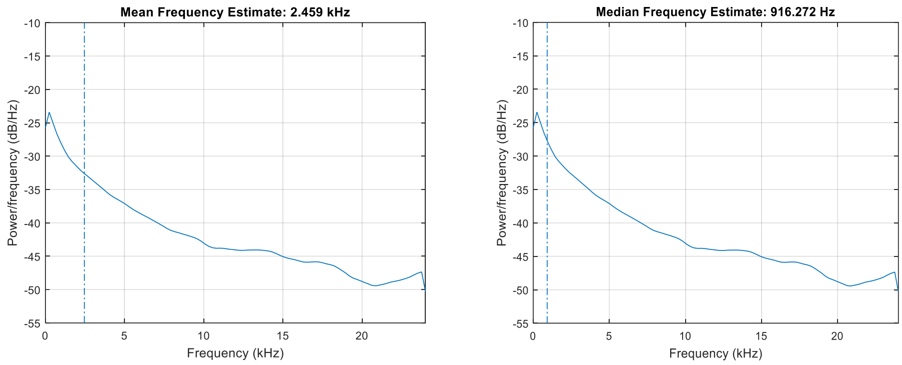
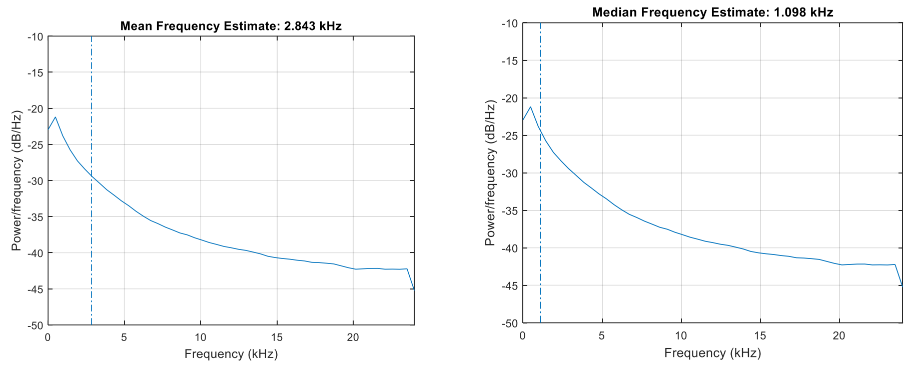


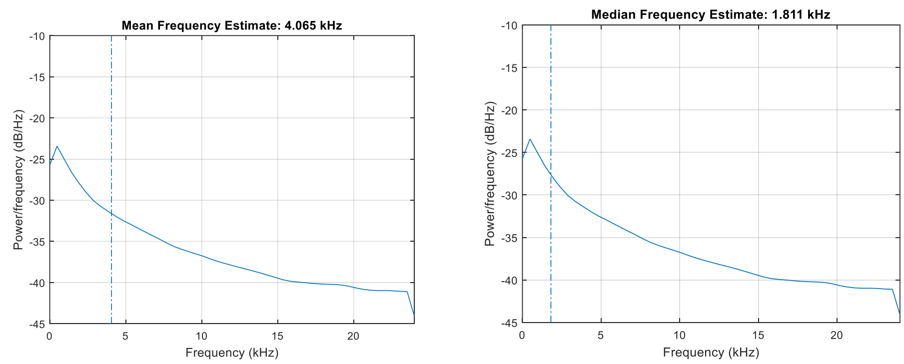
(a) mean and median frequencies estimation on the output of SVD (normal case)



(b) mean and median frequencies estimation on the output of SVD (abnormal case)



(c) mean and median frequencies estimation on the output of DWT (normal case)



(d) mean and median frequencies estimation on the output of DWT (abnormal case)

Figure 6. Statistical measures

Presentation of the Results:

Mean and median frequency estimation are measured for all cough cases on the output of both SVD and DWT. Results of calculations are presented in Tables 2 and 3. In Table 2, values of the median frequency estimation measures applied to the output of SVD, are shown. These resulted values are plotted in Fig. 7, where the cases are arranged in an ascending order based on the ages of participating patients. Age groups were already defined in Table 1. The values of the median frequency estimation measures applied to the output of DWT are tabulated in Table 3 and plotted in Fig. 8.

Table 2. The values of the mean and median frequency estimation measures applied to the output of SVD

Cases	Age Group	(Normal)		(Abnormal)	
		Mean	Median	Mean	Median
1	1	1736	582	1522	626
2	1	2217	724	1906	739
3	2	1716	552	2459	916
4	4	1804	777	1669	707
5	6	1911	747	2807	1193
6	6	2842	1029	2122	735
7	7	3808	1333	1477	580
8	7	3343	1057	3718	1579
9	8	3270	1237	2337	1013
10	8	3047	1143	2446	933
11	8	2906	1341	3262	1248
12	9	2252	870	2323	913
13	9	2579	991	1771	643
14	11	1776	630	2839	1056
15	12	1569	540	2661	912
16	14	1838	700	2251	1000
17	15	1474	507	2647	955
18	16	2242	839	2370	929
19	17	2490	1102	2439	937
20	18	1901	837	1667	595

Table 3. The values of the mean and median frequency estimation measures applied to the output of DWT

Cases	Age Group	(Normal)		(Abnormal)	
		Mean	Median	Mean	Median
1	1	2678	1156	2535	1248
2	1	3529	1428	3121	1470
3	2	3004	1545	2795	1405
4	4	3051	1482	4372	2325
5	6	4730	2048	3239	1444
6	6	5346	2461	2499	1158
7	7	4910	2038	6353	3129
8	7	5236	2417	3819	2009
9	8	3742	1672	3914	1833
10	8	4702	2644	4426	2335
11	8	3728	1728	3625	1791
12	9	3167	1670	2777	1188
13	9	4017	1950	2879	1279
14	11	2549	1075	3904	1764
15	12	2968	1386	3770	1979
16	14	2468	1012	4327	1876
17	15	2842	1098	4065	1811
18	16	4267	2165	4186	1853
19	17	4014	2174	3715	1837
20	18	4017	1950	2879	1279

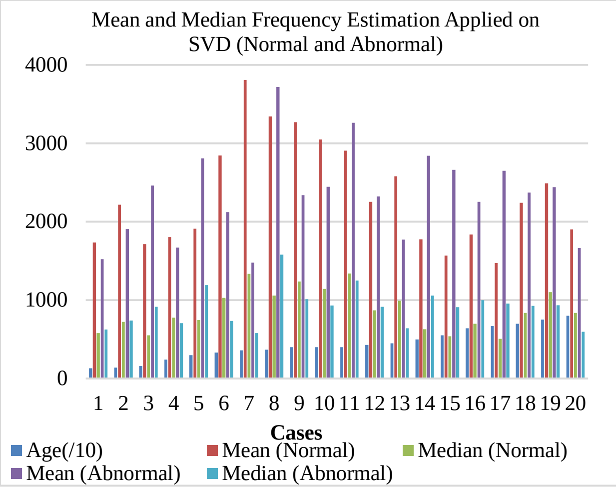


Figure 7. Statistical measures applied on the output of SVD

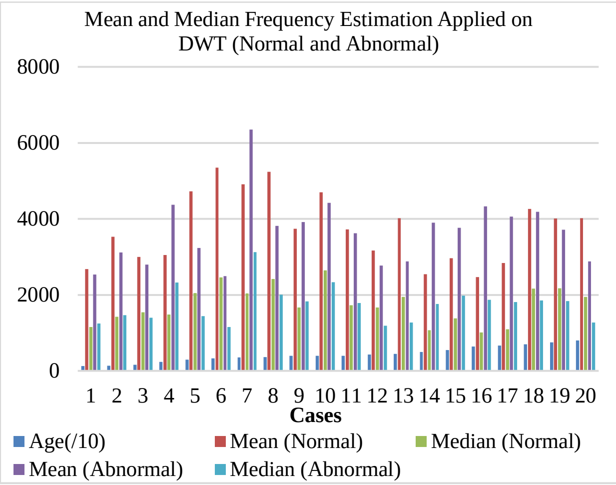


Figure 8. Statistical measures applied on the output of DWT

Discussion:

With reference to Fig. 7 and Fig. 8, it's possible to observe and discuss a number of points. In Fig. 7, which shows the statistical measures applied on the output of singular value decomposition (SVD), the mean and median frequency estimations, taken from Table 2, are plotted for the 20 considered cases. First point to mention about this figure is that values of mean and median start with a consistent increase for the age groups of young adults, while it exhibits a decrease for old adults. Maximum values can be roughly related to middle aged adults. The point to register is that mean values are higher than those of median values for all cases (both normal and abnormal). In the young and middle-aged adults, the mean values for normal cases are almost always higher than the mean values of abnormal cases. For old adults, however, the situation is reversed. On the other hand, median values shown in Fig. 7, are virtually close to each other, and hence it is difficult to acknowledge a featured observation about their relativity to age groups as well as normal and abnormal COVID-19 related cases.

The application of DWT is basically to compress the considered data and therefore targeting the more effective part, in order to generate effective features. In Fig. 8, the mean and median frequency estimation values are generally exhibiting a noticeable difference for both normal and abnormal cases, which is a positive and helpful research output serving the research targets and hence leading to improve the detection process. For all cases, the values of mean for normal cases are generally more than those of the abnormal cases, apart from three cases lying in the region of old adults age groups. Mean values, in contrast, are having minor differences between the normal and abnormal cases. Median values for normal cases are in general higher than the abnormal cases. Three cases in the old adult age groups are exhibiting an exception, where median values of the normal patients are lower than those of the infected participants.

Although the algorithm has performed efficiently, we have to mention that the work conducted in this paper offers preliminary results, and it is required to increase the number of cases in future to further validate the method and increase the reliability and trustworthiness.

Conclusion:

A proposed approach of COVID-19 coughs recognition based on the combination of SVD and DWT is implemented in this research. This approach exploits the characteristics of both SVD and DWT to generate an efficient approach for cough recognition. Difficulty of obtaining distinguished cough patterns for infected people, with respect to noninfected due to the similarity of cough characteristics, showed negligible effect on the performance of the algorithm. In singular value decomposition (SVD), just a small number of the values are used to represent the cough signal. Then applying discrete wavelet transform (DWT) has reduced the effective features to half of the input data. SVD reduced the number of values from 40000 to 200, while DWT reduces the number of values from 200 to 100, so finally this approach reduces the number of operations to only 200 times for any processed case. Applying mean and median frequency estimation leading to efficient statistical measures that generate an effective cough recognition rate. Finally, it is difficult to master and recognize exactly between normal and abnormal cases considering that some of the normal cases have other repertory diseases. Despite this challenging fact, diagnosis results obtained from the application of the proposed approach show high diagnosis rate. This is validated through the matching with relevant PCR tests. We trust, that the approach is open for more improvements with its performance further assured by enlarging the data set, while including healthy people.

Authors' declaration:

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are mine ours. Besides, the Figures and images, which are not mine ours, have been given the permission for re-publication attached with the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee in Al-Qalam University College.
- Ethics Approval: The work was approved by Kirkuk general hospital (344 on 2nd May 2021).

Authors' contributions statement:

T.S.M, and K.M.A made considerable contributions to the conception and design of study, applying computing techniques for experimentation and data analysis. K.M.A and M.S.A applied computing techniques for experimentation and data analysis. A.I.S and H.I.S made considerable contributions to the conception and design of study, participated with a considerable contribution to acquisition of data.

All team members made significant contribution to drafting the manuscript critically for important intellectual content, contributed substantially in interpretation of data and result discussion, helped significantly in the approval of the version of the manuscript to be published, and agreed to be accountable for all aspects of the work in terms of accuracy and integrity.

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تشخيص COVID-19 باستخدام التحليل الطيفي والإحصائي لتسجيلات السعال بناءً على مزيج من SVD و DWT

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الخلاصة:

تستخدم الإشارات الصوتية التي يولدها جسم الإنسان بشكل روتيني من قبل التخصصين في البحوث والتطبيقات الصحية للمساعدة في تشخيص بعض الامراض أو تقييم تقدم المرض. وبالنظر إلى التقنيات الجديدة ، من الممكن في الوقت الحاضر جمع الأصوات التي يولدها الإنسان ، مثل السعال. ويمكن بعد ذلك اعتماد تقنيات التعلم الآلي المستندة إلى الصوت من أجل التحليل التلقائي للبيانات التي تم جمعها مما يوفر معلومات قيمة غنية من إشارة السعال واستخراج الميزات الفعالة من فترة زمنية محدودة الطول تتغير كدالة للوقت. في هذا البحث يتم اقتراح وتقديم خوارزمية للكشف عن COVID-19 وتشخيصه من خلال معالجة السعال الذي يتم جمعه من المرضى الذين يعانون من الأعراض الأكثر شيوعًا لهذا الوباء. تعتمد الطريقة المقترحة على اعتماد مزيج من تحليل القيمة المفردة (SVD) وتحويل المويجات المنفصل (DWT). وقد أدى الجمع بين هاتين التقنيتين لمعالجة الإشارات إلى اتباع نهج جيد للتعرف على السعال ، حيث يولد ويستخدم الحد الأدنى من الميزات الفعالة. وفي هذه الخوارزمية المقترحة يتم تطبيق الترددات المتوسطة (mean and median)، والمعروفة بأنها أكثر الميزات المفيدة في مجال التردد ، لإنشاء مقياس إحصائي فعال لمقارنة النتائج. بالإضافة إلى الحصول على معدل كشف وتمييز عاليين ، تتميز الخوارزمية المقترحة بكفاءتها حيث يتم تحقيق تخفيض 200 مرة، من حيث عدد العمليات. على الرغم من حقيقة أن أعراض الأشخاص المصابين وغير المصابين في الدراسة بها الكثير من أوجه التشابه ، فإن نتائج التشخيص التي تم الحصول عليها من تطبيق نهجنا تُظهر معدل تشخيص مرتفعًا، والذي تم إثباته من خلال مطابقتها مع اختبارات PCR ذات الصلة. نعتقد أنه يمكن تحقيق أداء أفضل من خلال توسيع مجموعة البيانات ، مع تضمين الأشخاص الأصحاء.

الكلمات المفتاحية: فيروس كورونا، صوت السعال؛ كوفيد -19 ؛DWT، استخراج الميزات، معالجة الإشارات؛ تحليل احصائي، SVD.