A cardiac sound characteristic waveform method for in-home heart disorder monitoring with electric stethoscope

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Abstract

An analytical model based on a single-DOF is proposed for extracting the characteristic waveforms (CSCW) from the cardiac sounds recorded by an electric stethoscope. Also, the diagnostic parameters \([T1, T2, T11, T12]\), the time intervals between the crossed points of the CSCW and an adaptive threshold line (THV), were verified useful for identification of heart disorders. The easy-understanding graphical representation of the parameters was considered, in advance, even for an inexperienced user able to monitor his or her pathology progress. Since the diagnostic parameters were influenced much by a THV, the FCM clustering algorithm was introduced for determination of an adaptive THV in order to extract reliable diagnostic parameters. Further, the minimized \(J_m\) and \([v_1, v_2, v_3, v_4]\) could be also efficient indicators for identifying the heart disorders. Finally, a case study on the abnormal/normal cardiac sounds is demonstrated to validate the usefulness and efficiency of the cardiac sound characteristic waveform method with FCM clustering algorithm. NM1 and NM2 as the normal case have very small value in \(J_m\) (<0.02) and the centers \([v_1, v_2, v_3, v_4]\) are about [0.1, 0.1, 0.8, 0.4]. For abnormal cases, in case of AR, its \(J_m\) is very small and the values of \([v_1, v_3, v_4]\) are very high comparing to the normal cases. However, in cases of AF and MS have very big values in \(J_m\) (>0.38).

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Keywords: Electric stethoscope auscultation; Cardiac sound characteristic waveform (CSCW); Primary health care; Automatic data processing; Heart murmurs disorder

1. Introduction

The death due to heart disease in the world became to the second mortality after the stroke (cerebrovascular accident) since 1985. Furthermore, based on a medical certificate of death the majority of deaths caused by cardiac diseases are of the heart failure and coronary heart disease. However, except the identified diseases due to the cardiac diseases still 30% deaths are of unknown causes. Some of them might be due to the cardiac diseases. If life-style related diseases could not be monitored continuously during a long period, some cardiac diseases like coronary heart disease, angina pectoris and myocardial infarction might be difficult to be diagnosed appropriately and detected in an early step.

In the recent year, the high concern about health management and medical welfare makes the rapid development of home medical instruments for health care and diagnosis in daily life. Stethoscopes, in addition to other health care instruments such as weight scale, a clinically thermometer and a sphygmomanometer, have come into wide use for inexperienced users. Since the stethoscope could auscultate the respiratory sounds, lung sounds as well as cardiac sounds, and screen the most cardiorespiratory disorders and diseases, it might become a cheap and efficient home health care instrument in the near future. Recently the stethoscope has been used for auscultating embryonic (including fetal) cardiac sounds from pregnant mothers or for health management of pets in home. However, using the stethoscope to screen human’s disorder needs a long-term practice and experience. Even for a well-trained young cardiologist to auscultate and diagnose cardiac diseases several years’ clinic experience is required. Actually a well-experienced cardiologist could hear out the pathologic heart murmur very sensitively but it is so difficulty to an inexperienced or non-clinical experience person. Therefore, if the heart sound could be recognized or diagnosed with the support of computer software technique, the above problems will be solved and the stethoscope may be taken advantage of as a high-quality home medical and health care instrument.

The researches on diagnosis of heart diseases were concentrated around in the 1970s and there are a lot of results reported (Yoshimura, 1973; Machii, 1972; Yokoi, 1974; Iwata,
Easily estimated by these diagnostic parameters. Method, so that the normal or abnormal cardiac sounds can be derived from the cardiac sound waveform (CSCW) parameters, which could be used in diagnosis of heart disorder, characteristic waveforms from the cardiac sounds. The model based on a single-DOF is proposed for extracting their normal or abnormal directly by an untrained general user, sometimes even an inexperienced physician. An analytical method for in-home cardiac disorder detection and monitoring with a simple electric stethoscope. The heart sound analysis method for primary screening examination, and becomes stronger for the general users to perform the auscultation at home. Improvement in cardiac auscultation skill is still very strong in the screening examination, and becomes stronger for the general users to perform the auscultation at home.

The objective of this paper is to develop a novel cardiac sound analysis method for in-home cardiac disorder detection and monitoring with a simple electric stethoscope. The heart sounds are usually very difficult to be heard out whether it is in normal or abnormal directly by an untrained general user, sometimes even an inexperienced physician. An analytical model based on a single-DOF is proposed for extracting their characteristic waveforms from the cardiac sounds. The parameters, which could be used in diagnosis of heart disorder, are then derived from the cardiac sound waveform (CSCW) method, so that the normal or abnormal cardiac sounds can be easily estimated by these diagnostic parameters. Easy-understanding graphical representations are considered in advance for an inexperienced user to monitor his or her pathology progress. Furthermore, several examples of normal and abnormal cardiac sounds, which are included in the medical text books or internet web site (Sawayama, 1994; Nakao) and recorded directly by an electrical stethoscope system, are tested to validate the proposed characteristic waveform method. The diagnostic parameters defined by the time durations on and between the first and second sounds, and calculated from the characteristic waveforms are described in detail. Since these parameters are influenced much by a threshold valve (THV), the Fuzzy C-means (FCM) clustering algorithm is, thereon, introduced for determination of an adaptive THV. The results show that the diagnostic parameters can be obtained in an acceptable way by the FCM method. Finally, a case study on the abnormal/normal cardiac sounds is demonstrated to validate the usefulness and efficiency of the cardiac sound characteristic waveform method with FCM clustering algorithm.

2. Auscultation of heart sound

Auscultation denotes the act of analyzing sounds in the body that is produced in response to mechanical vibrations generated in the organs. The heart sounds are primarily generated from blood turbulence. The blood turbulence occurs due to fast accelerations and retardations of the blood in the chambers and arteries caused by the contraction or closure of the heart valves, which in turn produce mechanical vibrations that propagate through the body tissues up to the surface of the thorax. The heart sounds recorded by an electrical stethoscope are converted to digital signals and plotted in Fig. 1 as an example. Fig. 1(a) shows a normal sound waveform and Fig. 1(b) is an abnormal case of mitral regurgitation. It is obvious that the first and second sounds appeared clearly in the normal cardiac sound (Fig. 1a), but they seems to be difficult to distinguish each other in the abnormal mitral regurgitation because of the noise signal occurred serious between the first and second sounds (Fig. 1b).

Fig. 1. Heart sound examples. (a) Normal sound and (b) abnormal case of mitral regurgitation.

1979; Hunada, 1971; Yoshimura, 1971; Iwata, Suzumura & Ikegaya, 1977; Adolph, Stephens & Tanaka, 1970; Yogananth, Gupta, Udawadia, Miller, Corcoran & Sarma, 1976). Yoshimura (1973) discussed disease diagnostic system using the difference of threshold in phonocardiogram. Machii, (1972); Yokoi, (1974) showed the phonocardiogram diagnosis on screening examination, Yokoi, (1974) proposed an automated diagnosis system using information of maximal pulse width and zero-crossing rates (ZCRs) during a certain length of time. However, the studies on cardiac sound analysis were showed a rapid decrease after the 1970s because of the development of the techniques on the cardiologic echocardiography and cardiac catheterization or percutaneous coronary intervention (PCI), which provide a closer and accurate examination. Recently, with the high development of computer hardware and digital signals processing techniques, the cardiac sounds could be easily recorded and analyzed, the research on automatic cardiac sounds analysis (Akay, 1994; Kanai (1995), Wu, Lo & Wang, 1995; Bulgrin, Rubal, Thompson & Moody, 1993; Barschdorff, 1995; Ester, Femmer & Most, 1995) showed its new tendency. Most of these researchers were concerning on the characteristic extraction by frequency analysis method (Akay, 1994; Kanai, 1995; Wu et al., 1995; Bulgrin et al., 1993). Some others were on how to extract of the heartbeat from weeping noises of a baby (Barschdorff, 1995) and the noise cancellation by an adaptive filtering method (Ester et al., 1995). Those researches were mainly concentrated on how to help the cardiologist having more accurate diagnosis.

A report (Danford, Nasir & Gumbiner, 1993) showed that among the patients who had heart murmurs and were referred by primary care physicians, just about 25% of them could be found out to have pathology directly by echocardiography retesting or closer examination. This means that an expensive testing based on clinical assessment such as the Cardiologic Echocardiography and the PCI is probably not cost-efficient prior to the primary screening examination. Nevertheless, screening for heart disease by cardiac auscultation remains its importance for general daily health care, prescreening for heart disease prior to participation in athletics and so on. However, the proficiency in cardiac auscultation among physicians is getting in decline. The need for the primary care physicians to improve the cardiac auscultation skill is still very strong in the primary screening examination, and becomes stronger for the general users to perform the auscultation at home.

The objective of this paper is to develop a novel cardiac sound analysis method for in-home cardiac disorder detection and monitoring with a simple electric stethoscope. The heart sounds are usually very difficult to be heard out whether it is in normal or abnormal directly by an untrained general user, sometimes even an inexperienced physician. An analytical model based on a single-DOF is proposed for extracting their characteristic waveforms from the cardiac sounds. The parameters, which could be used in diagnosis of heart disorder, are then derived from the cardiac sound waveform (CSCW) method, so that the normal or abnormal cardiac sounds can be easily estimated by these diagnostic parameters. Easy-understanding graphical representations are considered in advance for an inexperienced user to monitor his or her pathology progress. Furthermore, several examples of normal and abnormal cardiac sounds, which are included in the medical text books or internet web site (Sawayama, 1994; Nakao) and recorded directly by an electrical stethoscope system, are tested to validate the proposed characteristic waveform method. The diagnostic parameters defined by the time durations on and between the first and second sounds, and calculated from the characteristic waveforms are described in detail. Since these parameters are influenced much by a threshold valve (THV), the Fuzzy C-means (FCM) clustering algorithm is, thereon, introduced for determination of an adaptive THV. The results show that the diagnostic parameters can be obtained in an acceptable way by the FCM method. Finally, a case study on the abnormal/normal cardiac sounds is demonstrated to validate the usefulness and efficiency of the cardiac sound characteristic waveform method with FCM clustering algorithm.

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Fig. 1. Heart sound examples. (a) Normal sound and (b) abnormal case of mitral regurgitation.
Basic heart sounds mostly occur in the frequency range of 20–200 Hz. Some heart murmurs produce the sound around 1 kHz. The first heart sound (S1) is generated at the end of atrial contraction, just at the onset of ventricular contraction. This sound includes the information of mitral valve closure and tricuspid valve closure. The second heart sound (S2) corresponds to the closure of the aortic valve (A2) and pulmonary valve (P2). The third heart sound (S3) and the fourth heart sound (S4) correspond to the cessation of ventricular filling and the atrial contraction, respectively. They appear at very low amplitudes with low frequency components (Fig. 2a) and are difficult to be caught in usual auscultation. In general cardiac sound auscultation (Ammash & Warnes, 2001; Christini & Glass, 2002; Reichlin, Dieterle, Camli, Leimendstoll, Schoenenberger & Martina, 2004; Hasfjord, 2004; O’Grady & O’Sullivan; Clinical examination of the heart; Cardiology), the murmurs patterns could be classified into several types as shown in Fig. 2. In the normal case the information on the first sound S1 and the second sound S2 are enough to describe the heart situation (Fig. 2b). For a systolic ejection murmur (Fig. 2c) and a pansystolic murmur (Fig. 2d) the noise signals appear between the S1 and S2 with different noise patterns. Furthermore, the two abnormal sounds, aortic stenosis and mitral regurgitation in Fig. 2 (c) and (d), respectively, show their second heart sound (S2) includes the sounds due to the closure of the aortic valve (A2) and pulmonary valve (P2). However, in most of the heart sound analysis, the information of the first heart sound and the second heart sound are playing an important rule in cardiac auscultation. Therefore, an important problem in the heart sound analysis comes how to extract the patterns from a time domain sound waveform.

3. Cardiac sound characteristic waveform method

3.1. Cardiac sound characteristic waveform extraction

It is an amazing fact that a proficient cardiologist could recognize the disorder heart sound by the auscultation. But it is difficult for an inexperienced physician especially for a general untrained user to understand the heart normality or abnormality in cardiac sounds by the auscultation. This supports the conclusion that the training in auscultation is very important. However, even for the untrained users they can easily understand the normal cardiac sounds by ‘lub-dub’ (Purves, Orians & Heller, 1992) phonologically and the mitral regurgitation sound by ‘whooshing’. This could be explained that the low frequency sound or the duration of the sound pressure is sensitive to be caught up by the eardrum. Based on this consideration, a vibration model of single degree-of-freedom (DOF) is proposed to extract the duration of the sound acted on the eardrum.

Fig. 3 shows the schematic of single-DOF analytical model. Assume that the mass, the coefficient of the spring, and the damping coefficient of the damper in this model are \(m\), \(K_h\), and \(C_h\), respectively. Denote the cardiac sound recorded by the stethoscope as the input \(S\). The output response \(\eta\) is then given by

\[m\ddot{\eta} + C_h\dot{\eta} + K_h\eta = S,\]

Further, let \(\ddot{S} = \pm S/m\), \(p = \sqrt{K_h/m}\) and \(\xi = C_h/2\sqrt{mK_h}\), then Eq. (1) comes to:

\[\ddot{\eta} + 2\xi p \dot{\eta} + p^2 \eta = \ddot{S},\]

where \(p\) and \(\xi\) are the parameters related to resonant frequency and the damping rate, respectively. These parameters \(p\) and \(\xi\) can be selected as certain values to extract the characteristics of heart sounds.
of the normal and abnormal heart sounds. In following analysis the parameters are set by $p = 10$ Hz and $\xi = 70.7\%$ as default.

Fig. 4 shows the results when the sound signals in Fig. 1 are applied to the analytical model. The heavy lines describe the outputs ($\eta$) as the heart sounds ($S$) are first normalized by divided the original sound by their maximum ten-points average, and inputted to the analytical model. It is obvious that the heavy lines give more simple and conspicuous representation than the original sound signal, and are easy to be treated in data analysis. Hereinafter, the heavy line is called as the cardiac sound characteristic waveform (CSCW). The problem next to be solved is how to define the parameters that could be used as diagnostic indicators for identifying the normal and abnormal heart sounds automatically with the aid of computer.

### 3.2. Diagnostic parameters definition and graphic representation

As mentioned above, the first sound $S_1$ and the second sound $S_2$ play an important role in the cardiac auscultation. Therefore, a concept for defining the diagnostic parameters is described in Fig. 5 as follows. A threshold value (THV) is selected first at a suitable value, which might be changed dependently on the person individual or the type of pathology. The time intervals between the crossed points of the characteristic waveform on the threshold line are defined by $T_{1i}$, $T_{2i}$, $T_{11i}$, and $T_{12i}$ ($i = 1, 2, \ldots, N_i$) in a sequential order as shown in Fig. 5(a). $T_{1i}$ and $T_{2i}$ are the widths of the first sound $S_1$ and the second sound $S_2$ in $i$-th sequential data. Furthermore, $T_{11i}$ is the time interval between two abutted $S_1$, which indicates the heart beat rhythm condition. $T_{12i}$ is the time interval between $S_1$ and $S_2$, which could be an indicator to express the heart valvular murmurs. To make the parameters $[T_{1i}, T_{2i}, T_{11i}, T_{12i}]$ visually, a two-dimensional plot, scattergram, on $[T_{1i}, T_{2i}]$, and $[T_{11i}, T_{12i}]$, is introduced as shown in Fig. 5(b). In general case, the duration of a normal cardiac cycle $T_{11i}$ is about 0.8 s, the auricular systole or ventricular systole $[T_{1i}, T_{2i}]$ around 0.1 s and the duration of systole and diastole $T_{12i}$ is about 0.4 s (Purves et al., 1992; Farabee, 2001; Circulatory system; Karnath & Thornton, 2002). Suppose two circles represent the normal cardiac rhythms’

![Fig. 4. Plots of the sound signals ($S$) in Fig. 1 and their characteristic waveforms ($\eta$), $p = 10$ Hz and $\xi = 70.7\%$.][1]

![Fig. 5. Concept for defining the diagnostic parameters and their graphic representations. (a) Definition of the parameters $[T_{1i}, T_{2i}, T_{11i}, T_{12i}]$, (b) the scattergram and (c) the histogram of the parameters.][2]
areas, which centers are supposed at [0.1, 0.1] and [0.8, 0.4] as shown in Fig. 5(b). If the diagnostic parameters [T1, T2], and [T11, T12], are placed within these two circles, the heart sound could be identified as normal. Therefore, the scattergram will help users understanding their heart condition viscerally. Furthermore, for helping users or physicians to evaluate the cardiac rhythms quantitatively, the parameters are also described in a histogram as shown in Fig. 5(c). These graphical representations could be helpful for both the general users and physicians to monitor the cardiac pathology easily and discover the heart disorders at an early step.

3.3. Verification and problem

The diagnostic parameters based on the characteristic waveform are not only related to the types of heart disorder but also might be influenced by the hardware property of the stethoscope system, recording conditions, and individual difference. In this section, the validation of the proposed characteristic waveform method is investigated by some case studies.

3.3.1. Case of normal cardiac sounds

First, the normal cardiac sounds recorded by a self-produced wireless electric stethoscope are tested by the CSCW method. The parameters for the single-DOF analytical model are set at $p = 10 \, \text{Hz}$ and $\xi = 70.7\%$.

Fig. 6 shows two examples, which signals are collected from a healthy woman of age 22 with weight 49 kg (named as NM1) and a healthy man of age 28 with 72 kg (NM2). The threshold values are set manually at THVs = 25 and 40%, respectively in order to obtain a reasonable set of the diagnostic parameters $[T1, T2]$ and $[T11, T12]$ (Fig. 6a and d). Fig. 6(b) and (e) show the corresponding scattergrams. It is obvious that the plots of the parameters $[T1, T2]$ and $[T11, T12]$ are concentrated into two areas marked by the two circles, which centers are set at [0.1, 0.1] and [0.8, 0.4] based on the consideration mentioned in above section. In fact, these plots are surely influenced by the THV and also the individual difference, which will mention in the following section. Furthermore, looking at the histogram graphics in both cases, the subject NM2’s heart pumps so regularly just like a clock (Fig. 6f) and the subject NM1’s heart is in normal but has a little fluctuation in heart beating (Fig. 6c).

3.3.2. Case of abnormal cardiac sounds

In this section some abnormal cardiac sounds collected in the medical book (Sawayama, 1994) and online clinical training website (Nakao) are used for validation of the characteristic waveform method.

Atrial fibrillation/flutter (AF) is a cardiac rhythm disorder (arrhythmia). It usually involves a rapid cardiac cycles, in which the upper heart chambers (atria) are simulated to contact in a very disorganized and abnormal manner. Also, listening to the heart beating with a stethoscope shows an irregular rhythm. The beating pulse may feel rapid, irregular, or both. Sometimes the pulse is too slow. The original AF sound signal and the result obtained by the characteristic waveform method are represented in Fig. 7(a). The parameters $[T1, T2]$ and $[T11, T12]$ calculated at $\text{THV} = 30\%$ are also plotted in the scattergram (Fig. 7b) and the histogram (Fig. 7c). Actually the characteristic waveform involves the irregular third heart sound, but it is omitted in present analysis. Furthermore, one can find out the reverse flow heart murmurs due to uncompleted closure of the mitral valve from the characteristic waveform marked by boxes. As for the parameters $[T1, T2]$, the scattergram shows no abnormality because their plots are within the normal area circle. But the parameter $T11$ distributed along a wide region, which could be also confirmed by the histogram. This means, in other words, the arrhythmia can be monitored and identified by the parameter $T11$.

Fig. 8 shows another example when the characteristic waveform method is applied to the mitral stenosis (MS) disorder. Mitral stenosis (MS) is a condition in which the mitral valve is narrowed. This narrowing causes the valve not opening properly and obstructing blood flow through the left chambers. From the characteristic curve in Fig. 8(a), it could say that the stenotic sound is described clearly by the fluctuation between the first and second sounds. The parameters $[T1, T2]$ and $[T11,$
T12] calculated at THV = 40% are plotted onto their scattergram and histogram. It is found that these parameters are distributed widely over the whole range, [T1, T2] are covering from almost 0 up to 0.5 s, and [T11, T12] are scattering from 0.3 to 0.9 s. Further, these patterns are completely different from the normal case and the AF case discussed above. This means that mitral stenosis (MS) might be very easily distinguished by using the characteristic waveforms and the diagnostic parameters.

Last selected example shows the case of the aortic regurgitation (AR) disorder. The aortic valve is between the heart’s left ventricle and aorta. The leaflets of the aortic valve are forced open as the left ventricle contracts for pumping the blood into the aorta, and close as the ventricle has relaxed in order to prevent the blood flowing back. Aortic regurgitation (AR) usually generates a strong heart murmur during the blood flowing through the valve. Some people, who have AR, may not start to find out their symptoms for years before the condition goes worse suddenly.

T12] calculated at THV = 40% are plotted onto their scattergram and histogram. It is found that these parameters are distributed widely over the whole range, [T1, T2] are covering from almost 0 up to 0.5 s, and [T11, T12] are scattering from 0.3 to 0.9 s. Further, these patterns are completely different from the normal case and the AF case discussed above. This means that mitral stenosis (MS) might be very easily distinguished by using the characteristic waveforms and the diagnostic parameters.

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From above results, it can be surely concluded that the proposed cardiac sound characteristic waveform method provides an easy understanding graphic representations and an easy follow-up numerical parameters for detecting and monitoring the heart disorder.

However, the threshold values (THV) discussed in above analysis, were selected manually by the sense or experience of the analyzer. How to select the THV automatically is an important factor in the cardiac analysis with CSCW method because it is strongly related to the recording condition by the stethoscope hardware, personal difference, and so on.

4. Cardiac sound analysis by CSCW method with data clustering technique

4.1. Effect of the threshold value (THV) on the diagnostic parameters derivation

As shown above, the parameters [T1, T2, T11, T12] have a good potential for diagnosis and screening of the heart disorders. However, these parameters are depended significantly on a selected threshold valve (THV). A suitable THV should be selected with a consideration on the person individual or the type of pathology. Ideally, THV can be selected within the range from 0 to 100%, but the stethoscope hardware system, or recording conditions, personal gap might affect directly on the quality of cardiac sounds. Considering the limitation in personal differences, the selectable range of THV is better to be experientially selected within 10–70%. Fig. 10 shows an example of the plots of [T1, T2] and [T11, T12] when the parameters are calculated by three THVs, i.e. 15, 30, and 60% separately.
Comparing these three cases, the plots ‘□’ in case of THV = 15% are scattered very widely both on the planes of [T1, T2] and [T11, T12]. As for case of THV = 60%, the plots ‘○’ of [T1, T2] look acceptable but for [T11, T12] the counter are missed somehow. The plots ‘△’ in case of THV = 30% shows that all the data are concentrated in the dotted circles in both scattergrams.

From the results in Fig. 10, it could say clearly that the problem how to determine a threshold value should be solved before one wants to use the characteristic waveform method. Of course, one simple way in practice is to select a THV manually and calculate the parameters, and then check they are acceptable or not subjectively. If they are not acceptable, change to another THV and follow the same process. However, this process is very harsh for an untrained user or a busy physician. In following, an automatic selecting method for obtaining a suitable THV is proposed by the aid of so-called Fuzzy C-means (FCM) clustering method.

4.2. Fuzzy C-means (FCM) clustering method and data grouping

Data clustering method is a classification technique for discovering whether the individuals of a population fall into different groups. The idea is to measure multiple features in order to search any groupings in the data. There are several methods for data clustering, such as K-means clustering, Fuzzy C-means clustering, Mountain Clustering and Subtractive clustering (Hammouda, 2000). In this paper, the Fuzzy C-means clustering algorithm developed by Bezdek in the 1970s (Hammouda, 2000; Bezdek & Pal, 1992; Bezdek, Hathaway, Sabin, Tucker, Bezdek & Pal, 1992) is introduced for determining the threshold values.

Considering a data series of \( Z = \{z_1, z_2, ..., z_N\} \) to be clustered into \( C \) groups, where \( z_j = [z_{j,1}, ..., z_{j,k}, ..., z_{j,n}] \), the center \( v_i \) of the \( i \)-th clustered group can be defined by

\[
v_i = \frac{\sum_{j=1}^{n} (w_{ij})^m z_{j}}{\sum_{j=1}^{n} (w_{ij})^m}, \quad i = 1, 2, ..., C,
\]

where \( w_{ij} \) is the degree of belongingness specified by a fuzzy membership grades between 0 and 1 with the constrains \( \sum_{j=1}^{n} w_{ij} = 1, \forall j = 1, ..., n \); \( v_i \) is the cluster center of data group \( i \); \( m \in [1, \infty) \) is a weighting exponent. The Euclidean distance \( d_{ij} \) between the \( i \)-th cluster center and the \( j \)-th data point is then defined as

\[
d_{ij} = ||v_i - z_j||.
\]

The cost function for FCM clustering is given by

\[
J_m(W, V) = \sum_{i=1}^{C} \sum_{j=1}^{N} (w_{ij})^m (d_{ij})^2,
\]

where \( W = \{w_{ij}\} \) and \( V = \{v_j\} \). The algorithm to calculate the cluster centers \( \{v_j\} \) and the membership matrix \( \{w_{ij}\} \) works iteratively by minimizing Eq. (5) with an obtained \( w_{ij} \), which is calculated by the Euclidean distance obtained in the previous step using the following equation

\[
w_{ij} = \frac{1}{\sum_{k=1}^{C} (d_{ij}^m d_{kj}^m)^{(m-1)/2}}.
\]

The performance of FCM clustering method depends on the initial membership grade values. It is recommended to run the algorithm for several times, each starting with different values of membership grades. In following analysis, the weighting exponent \( m \) is set at 2 and the number of iteration \( \gamma \) and the cost function \( J_m \) are used for evaluation of the performance of the FCM algorithm.

Thinking to cluster the parameters [T1, T2, T11, T12] into four groups, each cluster center \( v_i \) can be obtained easily by following the FCM clustering algorithm if letting \( [z_1, z_2, z_3, z_4] \) as [T1, T2, T11, T12]. Imitating the scattergram, the data \( [z_1, z_2] \) and \( [z_3, z_4] \) are plotted in a two-dimensional way as shown in Fig. 11. Thereby, the cluster centers can be expressed by two-dimension vectors \( [v_1, v_2] \) and \( [v_3, v_4] \), which are marked as A and B in Fig. 11.

![Fig. 11. Scattergrams of the data [z1, z2] and [z3, z4]. (a) Two-dimension plots of data [z1, z2] with the center position [v1, v2] and (b) two-dimension plots of data [z3, z4] with the center position [v3, v4], which are marked as A and B, respectively.](image-url)
4.3. Determination of the threshold values by FCM clustering method

Table 1 shows the obtained cluster centers from a normal cardiac sound signal when the THV is varied from 10 to 70%. The cost function $J_m$ shows bigger values at THV = [10, 20, 70%] than those at THV = [30, 40, 50, 60%]. This means the data are scattering wider at a big value of the cost function $J_m$ than at a small value. Confirming the fact, all of the parameters $[T_1, T_2]$ and $[T_{11}, T_{12}]$ obtained at each THV from 10 to 70% with 10% step are plotted together in Fig. 12(a) and (b). In contrast, the data obtained only at small value of $J_m$, i.e. THV = [30, 40, 50, 60%], are plotted in Fig. 12(c) and (d). From Table 1 and Fig. 12, it could firmly conclude that the THV selected at the minimized cost function produces a reliable series of the parameters $[T_1, T_2, T_{11}, T_{12}]$.

The parameters $[T_1, T_2, T_{11}, T_{12}]$ are the crossed points of the characteristic curve on the threshold line, and they are stored into a series in turn from the first crossed point. This means there are four possibilities in combination as follows,

$$
\begin{bmatrix}
T_{1j} & T_{2j} & T_{11j} & T_{12j} \\
T_{12j} & T_{1j} & T_{2j} & T_{11j} \\
T_{11j} & T_{12j} & T_{1j} & T_{2j} \\
T_{2j} & T_{11j} & T_{12j} & T_{1j}
\end{bmatrix}
$$

Thereby, the cluster centers $\{v_i\}$ might have also four combinations corresponding to each data set $\{T\}$. However, the data set $\{T\}$ could be reduced to cases, i.e. $[T_1, T_2, T_{11}, T_{12}]$ and $[T_2, T_{11}, T_{12}, T_1]$ or $[T_{11}, T_1, T_2, T_{12}]$ and $[T_{12}, T_1, T_2, T_{11}]$, if two-dimensional plots $[z_1, z_2]$ and $[z_3, z_4]$ are considered. Suppose, if the first crossed point is starting at $T_2$, the sequential order of the data will be $[T_2, T_{11}, T_{12}, T_1]$. Rearranging the data of Fig. 12 into a series of $[T_2, T_{11}, T_{12}, T_1]$, the scattergrams respect to $[T_2, T_{11}]$ and $[T_{12}, T_1]$ are plotted in Fig. 13(a) and (b). Further, the results obtained only at

<table>
<thead>
<tr>
<th>THV (%)</th>
<th>$J_m$</th>
<th>$v_1$ (s)</th>
<th>$v_2$ (s)</th>
<th>$v_3$ (s)</th>
<th>$v_4$ (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>0.62866</td>
<td>0.1300</td>
<td>0.1170</td>
<td>0.534</td>
<td>0.384</td>
</tr>
<tr>
<td>20</td>
<td>0.14034</td>
<td>0.1140</td>
<td>0.1020</td>
<td>0.749</td>
<td>0.392</td>
</tr>
<tr>
<td>30</td>
<td>0.00932</td>
<td>0.0988</td>
<td>0.0768</td>
<td>0.751</td>
<td>0.348</td>
</tr>
<tr>
<td>40</td>
<td>0.00938</td>
<td>0.0844</td>
<td>0.0654</td>
<td>0.751</td>
<td>0.336</td>
</tr>
<tr>
<td>50</td>
<td>0.00919</td>
<td>0.0700</td>
<td>0.0529</td>
<td>0.752</td>
<td>0.326</td>
</tr>
<tr>
<td>60</td>
<td>0.00911</td>
<td>0.0556</td>
<td>0.0399</td>
<td>0.752</td>
<td>0.315</td>
</tr>
<tr>
<td>70</td>
<td>1.16464</td>
<td>0.0494</td>
<td>0.0387</td>
<td>0.842</td>
<td>0.374</td>
</tr>
</tbody>
</table>

Fig. 12. Scattergrams of $[T_1, T_2]$ and $[T_{11}, T_{12}]$: (a) and (b) are the plots at all THVs in Table 1, (c) and (d) are the results obtained only at the suitable THV = [30, 40, 50, 60%].
the minimized cost function, i.e. at THV = [30, 40, 50, 60%] are plotted in Fig. 13(c) and (d).

In general case, the centers [v3, v4], corresponding to [T11, T12], is larger than the centers [v1, v2], corresponding to [T1, T2]. Therefore, the data sequence of [T1, T2, T11, T12] or [T2, T11, T12, T1] can be identified by comparing the center values. For example, if v3 > v2 the data sequence will be [T1, T2, T11, T12] and if v2 > v4, the data sequence will [T2, T11, T12, T1].

4.4. Results and discussions

4.4.1. Case of normal cardiac sounds

Two normal examples, which data were shown in Fig. 6, were used first to explain the efficiency of the FCM clustering method. Fig. 14 shows the minimized value of the cost function J_m and the cluster centers [v1, v2, v3, v4] as a function of the threshold value (THV). The dotted lines indicate the adaptive area of THV for calculating the parameters [T1, T2, T11, T12]. It is shown that the lowest J_m are along the regions THVs = 20–40% for case NM1 and 15–60% for case NM2. The mean value of J_m along THVs = 20–40% is about 0.02212 at case NM1 and is 0.00657 along THVs = 15–60% at case NM2. Referring to the plots of the cluster centers [v1, v2, v3, v4], it is found that they almost keep constant in these regions. The mean values of the centers [v1, v2, v3, v4] are [0.06954, 0.07527, 0.75700, 0.37757] s, respectively, for case NM1, and [0.08969, 0.06917, 0.76980, 0.33950] s for case NM2. And the corresponding cardiac cycle can be calculated by the value v3, i.e. \( C_3 = \frac{60}{v_3} = 79.2602 \) beats/min for case NM1 and 94.6372 beats/min for case NM2.

Fig. 13. Scattergrams obtained by rearranging the data series of Fig. 12; (a) and (b) are the plots at all THVs in Table 1, (c) and (d) are the results obtained only at the suitable THV = [30, 40, 50, 60%].

Fig. 14. Plots of the minimized cost function J_m and cluster centers [v1, v2, v3, v4] as a function of the threshold value (THV) for normal heart sounds.
Next, one uses the threshold values (THVs) of 20–40% by each 10% step for case NM1 and THVs of 15–60% by each 10% step for case NM2 to calculate the parameters \([T1, T2]\) and \([T11, T12]\), and plots the obtained results of case NM1 (\(\Delta\)) and NM2 (\(\circ\)) in Fig. 15. It shows that these data are all grouped quite well at the adaptive THVs. It could be concluded that the FCM clustering method is an available tool for obtaining the reliable parameters \([T1, T2]\) and \([T11, T12]\) from the heart sound characteristic waveforms.

4.4.2. Case of abnormal cardiac sounds

Some more examples are shown for verification of the FCM clustering method when it is applied to abnormal heart murmurs. In contrast, the abnormal sound data for testing are of the atrial
Fig. 17. Scattergrams of abnormal heart sounds AF, MS and AR, which parameters [T1, T2] and [T11, T12] are calculated at the region of THVs = [16–46%, 45–66%, and 10–22%], respectively.

Fig. 18. Summary of Figs. 14 and 17, which could be used as the indicators to identify the heart disorders.
The diagnostic parameters were defined by the time durations on and between the first and second sounds, which was verified useful for identification of heart disorders. The easy-understanding graphical representation of the parameters was considered, in advance, even for an inexperienced user able to monitor his or her pathology progress. Since the diagnostic parameters were influenced much by a threshold valve (THV), the Fuzzy C-means (FCM) clustering algorithm was, thereon, introduced for determination of an adaptive THV in order to extract reliable diagnostic parameters. Further, the minimized cost function and the cluster centers could be also efficient indicators for identifying the heart disorders.

5. Conclusions

In this paper, a novel cardiac sound analysis method for in-home cardiac disorder detection and monitoring with a simple electric stethoscope was described. An analytical model based on a single-DOF was proposed for extracting their characteristic waveforms from the cardiac sounds so that the heart sounds could be easily treated by computer for screening heart disorder.

The diagnostic parameters were defined by the time durations on and between the first and second sounds, which was verified useful for identification of heart disorders. The easy-understanding graphical representation of the parameters was considered, in advance, even for an inexperienced user able to monitor his or her pathology progress. Since the diagnostic parameters were influenced much by a threshold valve (THV), the Fuzzy C-means (FCM) clustering algorithm was, thereon, introduced for determination of an adaptive THV in order to extract reliable diagnostic parameters. Further, the minimized cost function and the cluster centers could be also efficient indicators for identifying the heart disorders.
Finally, a case study on the abnormal/normal cardiac sounds is demonstrated to validate the usefulness and efficiency of the cardiac sound characteristic waveform method with FCM clustering algorithm.

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