

Heart Sound Analysis for Discrimination of VSD

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Abstract. A ventricular septal defect (VSD) is the most common congenital heart disease, which can be cured with a high probability if it is detected in an early stage. In our previous researches on heart sounds (HSs) analysis, the detection methods of heart disease using the cardiac sound characteristic waveforms in time domain or in frequency domain were proposed, and have been succeed in discriminating several heart murmurs. In this paper, we are going to apply these methods to detect VSD. Based on analysis results, a new approach by using the feature parameters both in time domain and in frequency domain is proposed to achieve higher discrimination rates.

1 Introduction

A VSD is one of the most common congenital heart disease, accounting for 0.24% of newborn babies [1,2], and it can be cured with a high probability if this disease is detected in an early stage. Recently, with the high development of computer technique and digital signal processing technology [3,6], more and more researches are concerning on the HSs analysis. Through comparative analysis, the simple and effective methods of our previous studies [4,6] were proposed to detect heart murmurs with higher classification accuracy. In this study, we are going to use our previous method to detect VSD from normal cases. According to experimental results, a new approach is proposed to achieve higher discrimination rates. The rest of the paper is organized as follows. Section2 introduces HSs acquisition and preprocessing. Section3 proposes HSs analysis method. Section4 presents discrimination analysis. Finally, the conclusions are summarized in Section5.

2 HSs Acquisition and preprocessing

Auscultation denotes the act of analyzing sounds in the body that is produced in response to mechanical vibrations generated in the organs. Therefore, for different heart murmurs, we should analyze HSs collected from different auscultation areas, while for VSD cases, it is reported that the HSs collected from tricuspid area can supply more important information [8]. In this study, analyzed HSs were collected from tricuspid area by the HSs acquisition system, meanwhile, sampling frequency F_s were set as 44.1 kHz. The basic HSs consist of two primary components which are often described as the first heart sound (S1) and second heart sound (S2). To analyze the useful information, wavelet decomposition (WD) is used as pre-processing for cancellation of the unwanted frequency components over 700Hz and below 20Hz. Daubechies type wavelet DB10 is used as a mother wavelet. Finally, the filtered signals, $x(t)$ with 21.5-689Hz is gained.

3 Cardiac sound analysis

In this section, firstly, the diagnostic features, $[T11, T12]$ from characteristic waveform (W_t) in time domain as detecting character of HSs are extracted. And then to experimental analysis, the diagnostic features $[Fg, Fw]$ extracted from the frequency characteristic waveform (W_f) are proposed to detect VSD. By analyzing the distribution of $[T11, T12]$ and $[Fg, Fw]$ for VSD and normal HSs. Finally, a new approach is proposed for detecting VSD and normal cases.

3.1. Time domain analysis

In our previous studies, time characteristic waveform analysis method [4] could realize detection of several heart diseases. So this method is used to analyze performance evaluation for discriminating VSD HSs and normal HSs, and the detailed is in following.

3.1.1. Characteristic waveform(W_t) extraction

Consider a data series $x(t)$, $t=1,2,\dots,N$, by WD for HSs, where N denotes the number of data. Then the W_t based on the Viola integral method is given by

$$w_t(\delta) = \frac{1}{2\delta} \sum_{n=t-\delta+1}^{t+\delta} [x(n) - \sum_{n=t-\delta+1}^{t+\delta} x(n)/2\delta]^2. \quad (1)$$

At last, the normalization is applied by setting the amplitude of W_t within 1.0. Since many experiments show that the duration of S1 or S2 is over than 0.06 second [4,8], we set $\delta=0.03 \times F_s=1323$. As an example, Fig.1 plots $x(t)$ daubed with gray and it's W_t . Fig.1(a) shows the case of normal sound and Fig.1(b) is VSD sound. As for the normal sound, W_t seems to have longer time interval between two abutted S1 and between S1 and S2 than VSD.

3.1.2. Diagnostic features definition and representation

As mentioned above, a concept for defining the diagnostic parameters is described in Fig.1(a) and (b). A threshold value (Thv1) is selected first at a suitable value, the time intersection between the crossed points of the W_t on the Thv1 line are defined by $a(S1_i), b(S1_i), a(S2_i)$ and $b(S2_i)$ ($i=1,2,\dots,N$) in a sequential order as shown in Fig.1. The center of gravity, especially denoted $G_t(S1_i)$ and $G_t(S2_i)$ as shown in Fig.1(a) and (b), the time index of $G_t(S1_i)$ and $G_t(S2_i)$ are gained by

$$G_t(Sk_i) = \sum_{n=a(Sk_i)}^{b(Sk_i)} n \times W_t(n)^2 / \sum_{n=a(Sk_i)}^{b(Sk_i)} W_t(n)^2, k=1, 2; i=1,2,\dots,N. \quad (2)$$

$T11_i$ is the time interval between $G_t(S1_i)$ and $G_t(S1_{i+1})$, $T12_i$ is the time interval between $G_t(S1_i)$ and $G_t(S2_i)$. To make the parameters $[T11_i, T12_i]$ visually, a two-dimensional plot, scatter gram, on $[T11_i, T12_i]$ is introduced as shown in Fig.1(c).

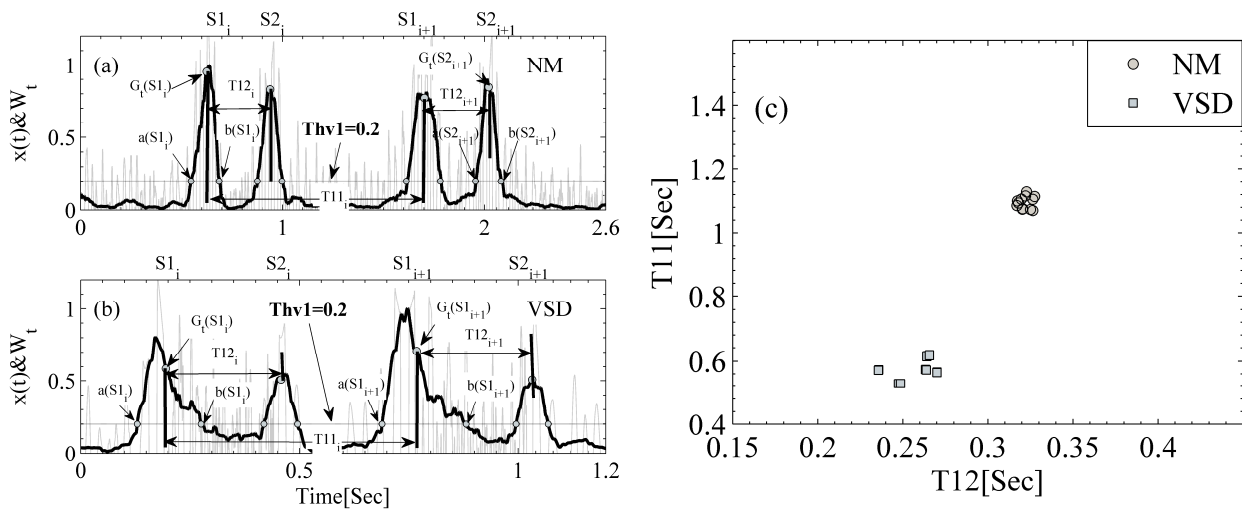


Fig.1. Concept for defining the diagnostic features $[T11, T12]$ from W_t and $[T11, T12]$'s representation by scatter diagram. (a) Normal sound case, (b) abnormal case of VSD and (c) $[T11, T12]$ distribution for NM and VSD cases.

3.1.3. Effects of Thv1 on $[T11, T12]$

By many experimental analysis, as for normal cases, when $Thv1$ is set as the interval $[0.2, 0.5]$, $[T11, T12]$ is almost not sensitive with $Thv1$. While as for VSD cases, when $Thv1$ is set as $[0.2, 0.4]$, there is a little influence on $[T11, T12]$, which can be negligible.

3.1.4. Experimental results and discussions

To validate the proposed method, in this paper, the used data set with 468 sound samples that consisted of 242 normal and 226 VSD cases. The normal cases were from 23 health students in university, the VSD cases were from 17 patients in hospital.

3.1.4.1 Case of normal HS

According to the distribution of $[T11, T12]$, generally, normal HSs could be divided into three types. Fig.2(a),(b) and (c) show the three typical examples collected from a health female of age 25 with weight 61 kg (NM1), a healthy male of age 26 with weight 72 kg (NM2), a male of age 23 with weight 68 kg (NM3), respectively. Furthermore, the data set of the diagnostic features $[T11, T12]$ are plotted in Fig.2(g), NM1 is marked by(■), NM2 (▼), and NM3(●).

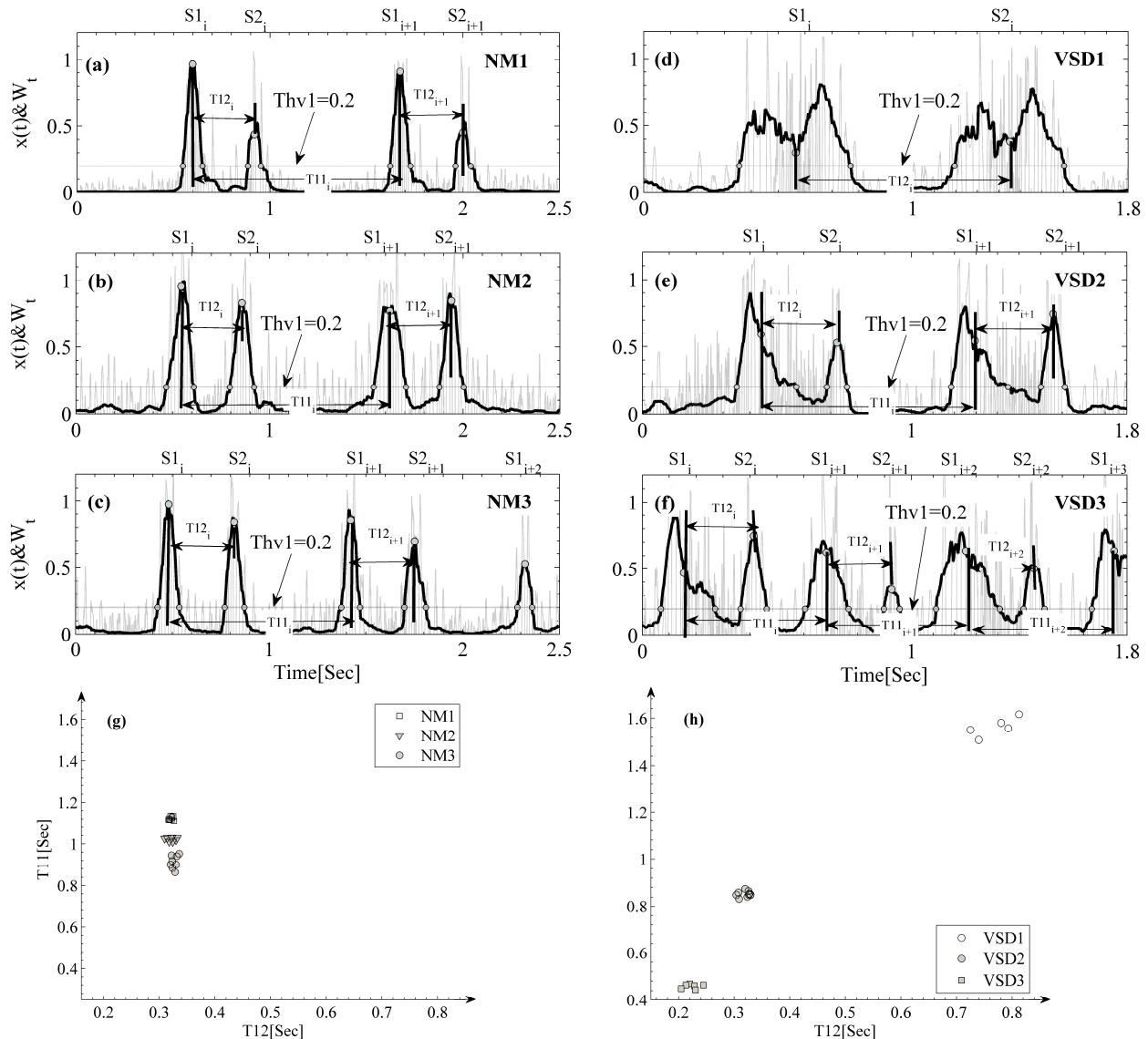


Fig.2. Plots of the W_t curves and $[T11, T12]$ extraction and the graphic representations of three kinds of normal heart sound signals(NM1,NM2,NM3) , and three kinds of VSD heart sounds(VSD1,VSD2,VSD3).

3.1.4.2 Case of VSD HS

However, for VSD cases, according to the strength of noise and the heart beat, VSD case generally can be divided into three types. The first type is that $S1$ and $S2$ can not be distinguished due to stronger noise which causes $[T11, T12]$ are far bigger than NM case, just as a VSD1 case collected from a male with VSD of age 12 and 32kg(Fig.2(d)). The second is that the noise almost not affect the $[T11, T12]$, just as VSD2 from female of age 7 with weight 30 kg (Fig.2(e)). The third is the

case with higher heart beat and heart noise, named VSD3 from a female of age 4 with weight 16 kg, the distribution of [T11,T12] are a far smaller than NM cases (Fig.2(f)). Furthermore, the data set of the [T11,T12] is plotted in Fig.2(h), VSD1 is marked by(○), VSD2(●), VSD3(■).

3.1.4.3 Summary

Analysis results show that there is the common region between VSD cases and NM cases, which includes 32.6% of NM cases and 29.1% of VSD cases, so it's impossible to distinguish VSD cases from NM cases. Next, frequency analysis method is proposed to detect normal and VSD cases.

3.2 frequency analysis method

The envelope curve method in frequency domain has been proved to recognize several heart murmurs in our previous studies [6]. Based on this point, a new characteristic waveform curve in frequency domain (W_f) is proposed to detect VSD. Consider a data series $x(t), t=1,2,\dots,N$, where, N denotes the number of data. Then $W_f(f=1,2,\dots,N)$ based on the Viola integral method is given by

$$w_f(\delta) = \frac{1}{2\delta} \sum_{k=f-\delta+1}^{f+\delta} \left| \left(\sum_{n=0}^{N-1} x(t) e^{-j\frac{2\pi}{N}kt} \right) \right|. \quad (3)$$

By many experiments, δ is set as 8. At last, the normalization is applied by setting the amplitude of W_f within 1.0. As an example, frequency distribution daubed with gray and W_f are plotted in Fig.3. Fig.3(a) shows a normal case and Fig.3(b) is a VSD case. W_f of the normal sounds, which has the lower density frequency component focused on a narrower region compared with VSD cases.

3.2.1 Features extraction and representation

Two diagnostic features, F_g and F_w are defined, which correspond to the frequency index of the center of W_f during interval $[0, (N-1)/2]$ and the frequency width of W_f on a $Thv2$ as shown in Fig.3(a) and (b). The representation of $[F_g, F_w]$ is introduced in Fig.3(c). Here, F_g is gained by

$$F_g = \sum_{k=0}^{(N-1)/2} kW_f(k) / \sum_{k=0}^{(N-1)/2} W_f(k). \quad (4)$$

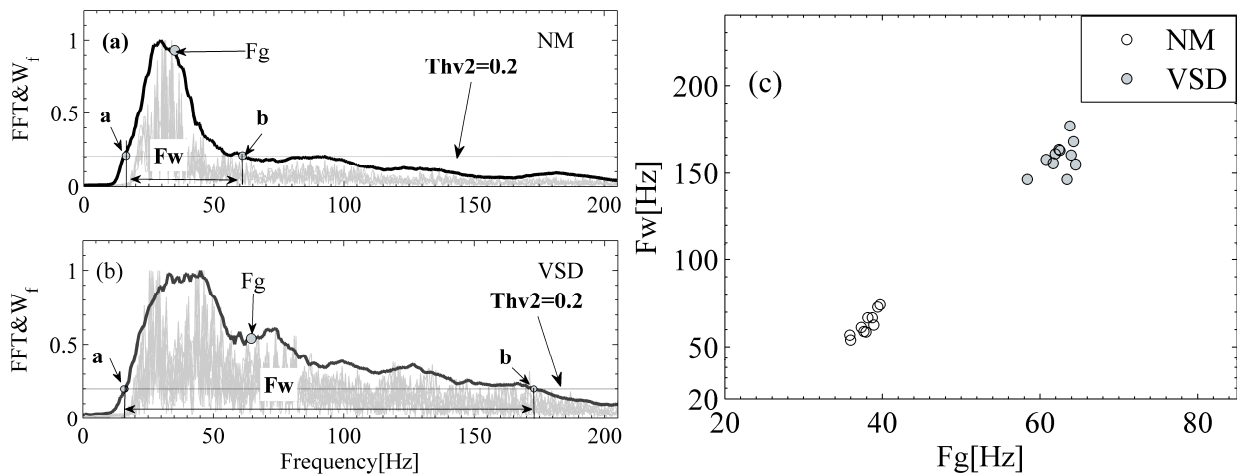


Fig.3. Concept for defining the diagnostic features $[F_g, F_w]$ from W_f curve and $[F_g, F_w]$'s representation by scatter diagram. (a) Normal sound case, (b) abnormal case of VSD and (c) $[F_g, F_w]$ distribution for NM and VSD cases.

By many experimental analysis, when $Thv2$ is selected in the interval $[0.1, 0.2]$. Generally, there are greater differences between NM cases and VSD cases. In this study, the $Thv2$ is set at 0.2.

3.2.2 Experimental results and discussions

Character of W_f as shown in Fig.4(a-f). Fig.4(g) and (h) show the data set of the $[F_g, F_w]$.

3.2.3 Summary

By analysis, the common region is extracted, which includes 38.4% of NM cases and 20.1% of VSD cases. So it's also impossible to distinguish VSD cases from NM cases using $[F_g, F_w]$. But by analyzing common region, the common region mainly consists of NM3 and VSD2 in time domain, while the common region in frequency domain mainly consists of NM1 and VSD3. So using $[T11, T12]$ & $[F_g, F_w]$ as new diagnostic features might discriminate VSD from NM cases.

4 Discrimination analysis using $[T11, T12]$ & $[F_g, F_w]$

The distributions of $[F_g, F_w]$ for the NM and VSD cases in $[T11, T12]$ common region are analyzed, the experimental results are showed in Fig.5. Fig.5(a) shows the $[T11, T12]$ in common region,

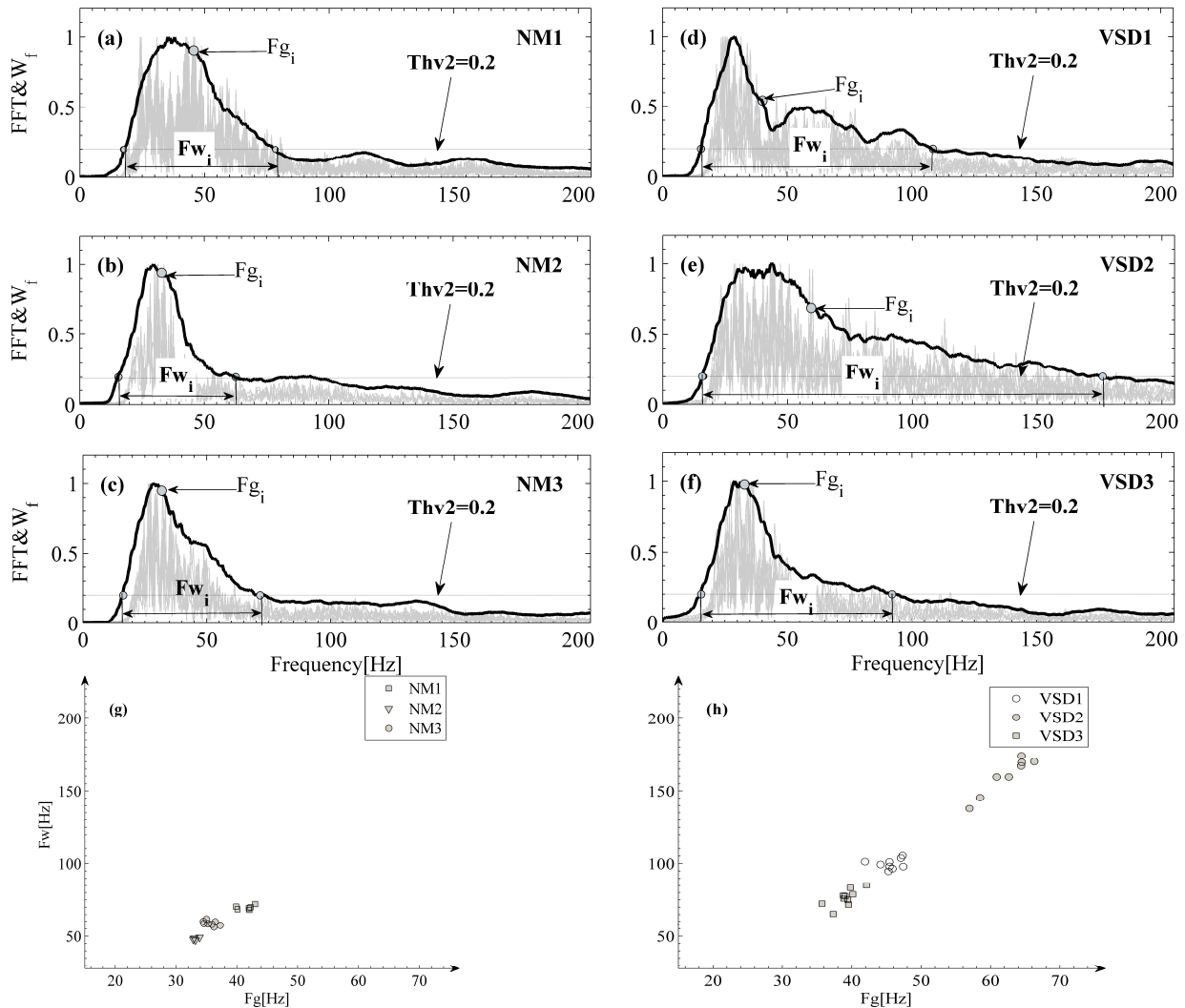


Fig.4. Plots of the Wf curves and $[F_g, F_w]$ extraction and the graphic representations of three kinds of normal heart sound signals (NM1, NM2, NM3), and three kinds of VSD heart sounds (VSD1, VSD2, VSD3)

which include 32.6% of total NM cases denoted NM_c, and 20.1% of total VSD cases denoted VSD_c and Fig.5(b) is the distributions of NM_c and VSD_c in $[F_g, F_w]$ domain, in $[F_g, F_w]$ common region, 3.4% of NM_c and 8.5% of VSD_c are included. So the higher discrimination rates for NM cases denoted DRN and VSD cases (DRV) are gained by

$$DRN = 1 - 32.6\% \times 3.4\% = 98.89\%; \quad DRV = 1 - 29.1\% \times 8.5\% = 97.53\%. \quad (5)$$

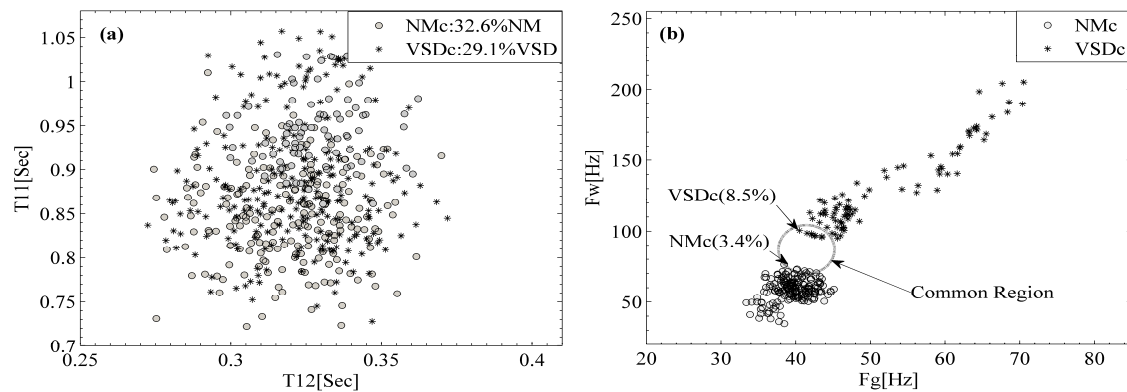


Fig.5. (a) is the graphic representations of the data set $[T11, T12]$ for VSD and NM cases in common region and (b) shows $[Fg, Fw]$ representation corresponding to Fig.5(a) heart sounds

5 Conclusion

In this study, the character waveform method for discriminating VSD and NM cases was presented in detail. At first, the WD was used for retaining the frequency components between the interval $[20, 700]$ Hz. Next, two diagnostic features $[T11, T12]$ extracted from W_t were defined for detecting VSD. A case study on the normal and VSD sounds was demonstrated to validate the usefulness and efficiency of W_t . Based on analysis results for discriminating NM and VSD cases, in frequency domain, $[Fg, Fw]$ extracted from W_f were defined as diagnostic features for detecting VSD cases. By analyzing the distribution of $[T11, T12]$ and $[Fg, Fw]$, a new approach using $[T11, T12] \& [Fg, Fw]$ as diagnostic features for detecting VSD and normal cases was proposed. Experimental results showed discrimination rate are $DRN=98.89\%$, $DRV=97.53\%$, respectively.

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