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CLASSIFICATION OF DOPPLER BLOOD FLOW SOUND DURING HEMORRHOIDAL ARTERY LIGATION USING MEL FREQUENCY CEPSTRUM COEFFICIENT AND SUPPORT VECTOR MACHINE

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Abstract. *In 1995, Morinaga et al. adopted the Doppler blood flow measurement technique to develop a novel surgical treatment for haemorrhoids, later known as the Doppler guided hemorrhoidal artery ligation (DG-HAL). During an artery search process, the surgeon is required to focus on the ultrasound produced by the Doppler instrument to perceive subtle changes indicating the presence of a target artery. However, the correct identification of haermorrhoidal arteries using ultrasound may sometimes be difficult because of several factors. The use of automated methods as a decision support system can help the DG-HAL practitioners in identifying hemorrhoidal arteries in better ways. However, the Doppler audio signal is not frequently recorded and investigated in the literature despite advancements in biological sound classification in recent years. Therefore, this paper proposes a Doppler blood flow sound classification method based on Mel frequency cepstrum coefficient (MFCC) features and support vector machine (SVM) classifier. Several MFCC input combinations to SVM, kernel functions, and SVM parameters are investigated to determine the best accuracy. The experiment results indicate that for cases of binary classification (arterial sound and non-arterial sound), a classification accuracy of 96.66% has been reached on a private database consisting of 100 sound samples.*

Keywords: Doppler blood flow sound, Classification, MFCC, SVM, DG-HAL

1. **Introduction.** Doppler ultrasound instruments have been widely used as a non-invasive means of evaluating blood flow parameters. Since the first demonstration by Satomura to measure blood flow velocity using Doppler effect principles, the technique has improved significantly [1]. In 1995, Morinaga et al. adopted the Doppler blood flow measurement technique to develop a novel surgical treatment for hemorrhoids, namely Doppler guided hemorrhoidal artery ligation (DG-HAL) [2]. Hemorrhoids is considered among the most prevalent anorectal disorders [3]. The surgical procedure involves the accurate identification and ligation of the superior rectal arteries carrying blood into haemorroidal tissues using specially designed proctoscope. The ligation of hemorrhoidal arteries reduces blood flow into hemorrhoidal venous plexi, gradually resulting in shrinkage of hemorrhoidal tissues [2]. To enable the procedure, the proctoscope is equipped with a Doppler transducer located in its outer wall and a ligation window located next to the transducer. DG-HAL has the advantage of less anal wounds and reduced fatal complications [4,5].

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The Doppler signal correlating with major trunks of hemorrhoidal arteries is searched by gently rotating and tilting the proctoscope along the circumference of the anal canal. When the transducer detects blood flow inside the hemorrhoidal artery, the Doppler instrument emits an audible output with specific pattern. However, the correct identification of haermorrhoidal arteries using ultrasound may sometimes pose difficulties to the surgeon performing DG-HAL. In particular, during arteries search process, the surgeon is required to focus on an ultrasound produced by Doppler instrument to perceive subtle changes indicating the presence of target artery. According to Mowatt et al., one problem with the usage of the Doppler ultrasound assessment in clinical practice was the interpretation of the audible output by the clinician [6]. The erroneous interpretation of Doppler ultrasound may be caused by poor training, lack of experience, and time constraints [7-9]. Inaccurate and inconsistent interpretation of the Doppler ultrasound may therefore contribute to the risk of recurrence and subject patients to unnecessary surgical time. Prolonged operative duration has also been linked with higher risk of complications [10]. Related to this, the presence of automated methods as a decision support system can be beneficial to the DG-HAL practitioner in identifying hemorrhoidal arteries in more intuitive ways.

As a matter of fact, the Doppler audio signal is rarely recorded and investigated [11]. This situation is limiting the systematic search of audio files and their associated research studies. However, still, a small number of studies regarding the Doppler sound exist with primary focus on Doppler sounds produced by blood flowing through the heart valves [12,13]. In the field of medicine, similar applications such as automatic analysis of heart, respiratory, and intestines sound have gained a higher interest and have been widely explored [14-16]. Doppler blood flow sound is a real-time audio signal that continuously changes in rhythm, frequency, and amplitude in line with blood flow cycle [11] and as it is known, blood flow is mainly regulated by the heart. Therefore, methods that have previously been used to perform automatic classification of heart sound have the potential to be employed to classify Doppler blood flow sound. The following part will discuss methods in heart sound classification.

Many features have been widely studied in the literature, and these can be summarized into three types: 1) time [17], 2) frequency [18,19], and 3) combined time-frequency features [20-22]. Extracting more discriminative features from the combined time-frequency is gaining more popularity in recent research. Among the proposed methods, wavelet transformation and the Mel frequency cepstrum coefficient (MFCC)-based features are most commonly used for heart sound feature extraction because of their effectiveness [23].

The artificial neural network (ANN) and support vector machine (SVM) are the classification methods that are widely used due to their advantages compared to others [24,25]. The ANN has an excellent ability to adapt to the complex nonlinear data as well as perform accurate and effective data classification. SVM, a relatively new classification method with high success rates, has been used as classification method in various application areas. One of the notable advantages is that the SVM classifier has a very stable output, even when the classifier is trained independently by random features [26].

Ortiz et al. [24] employed MFCC along with dynamic time warping (DTW) to serve as input to an SVM. They calculated mean and standard variations from MFCC coefficients to capture the spread of data distribution and realized a test score of 84%. Nogueira et al. [22] proposed MFCC-based features and motifs combined into a two-dimensional (2D) heat map representation. Then, they applied SVM as a binary classifier to both feature groups to separate between normal and abnormal heart sound signals. For comparison, they also evaluated convolutional neural network (CNN) and random forest (RF) classifiers, achieving the best results (accuracy of 86.96%) with the SVM with radial basis function (RBF) kernel.

As previously mentioned, the Doppler sound is rarely recorded and investigated. Specifically, the automatic recognition of the Doppler hemorrhoidal arterial blood flow sound has not been previously reported by other studies. Therefore, the purpose of this study is to conduct a preliminary experiment by using MFCC features and SVM classifier for developing an intelligent DG-HAL surgery device that can automatically recognize arterial Doppler blood flow sounds.

The key contributions of this paper are two-fold: 1) the use of newly recorded Doppler blood flow sound which would provide large dataset over time, and 2) the use of a Doppler blood flow sound classification algorithm that combines SVM and variances calculated from MFCC-based features as the inputs. In addition, studies on different kernel configurations and comparison with Naïve Bayes (NB) as probabilistic classifier are presented in this paper.

The remainder of the paper is structured as follows. Section 2 provides information about data sources, some basic principles related to the research, and conceptual framework. Section 3 presents classification performance under different classifier inputs and parameters. Section 4 concludes the research and offers direction for future work.

2. Materials and Methods.

2.1. Overview of the proposed algorithm. The proposed algorithm consists of three parts: signal preprocessing, signal representation based on MFCC, and SVM classification modeling. Figure 1 presents the complete flowchart of the proposed method. There are training and testing stages as commonly found in the supervised learning methods.

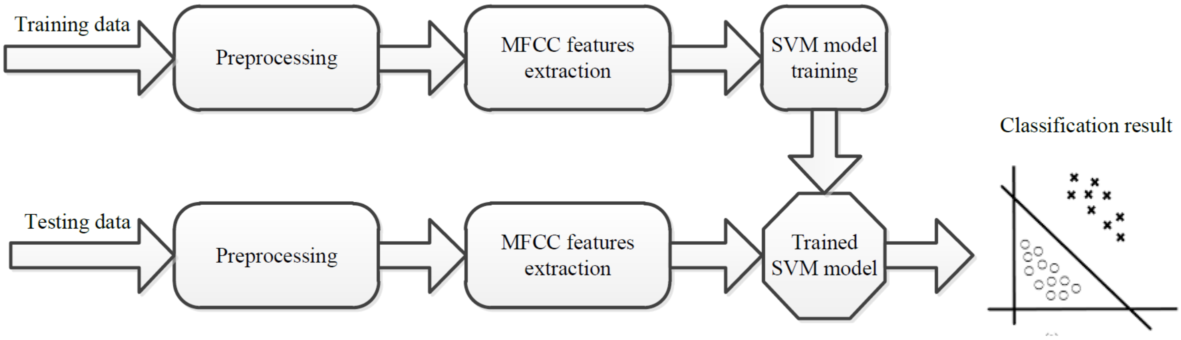


FIGURE 1. The flowchart of the Doppler blood flow sound classification consisting of the training and testing stages

During the training stage, the primary signal is first preprocessed which comprises downsampling, filtering, and normalization steps. The MFCC features of pulsing, wheezing, and thumping Doppler sound signals are then extracted to build training database. The MFCC features that have been previously labeled are fed into the SVM model and used as criterion data to facilitate classifier learning. During the testing stage, the testing sound signals are treated in the same way as in the training stage except they are fed to the trained model to evaluate the classification performance.

2.2. Dataset and signal preprocessing. Different Doppler signals are produced during DG-HAL procedure. Pulsing sound is caused by pulsatile blood movement through an artery, wheezing sound reflects non-pulsatile venous blood flow, and thumping sound arises from rubbing motion between transducer and rectal wall. The only sound that matters is the pulsing sound, indicating the presence of hemorrhoidal artery, which has middle-low frequency spectrum (up to 4 kHz) with pulsing amplitude. Later at classification, the pulsing sound will be categorized as arterial sound while the non-pulsing and thumping sounds will be categorized as non-arterial sound.

The Doppler signal is a complex signal that includes random phases due to scattering particles in the sample volume. The Doppler shift is generally in the range of 0.2-7.5 kHz. Figure 2 shows representations of the Doppler blood flow sound obtained from radial artery in time- and time-frequency domains.

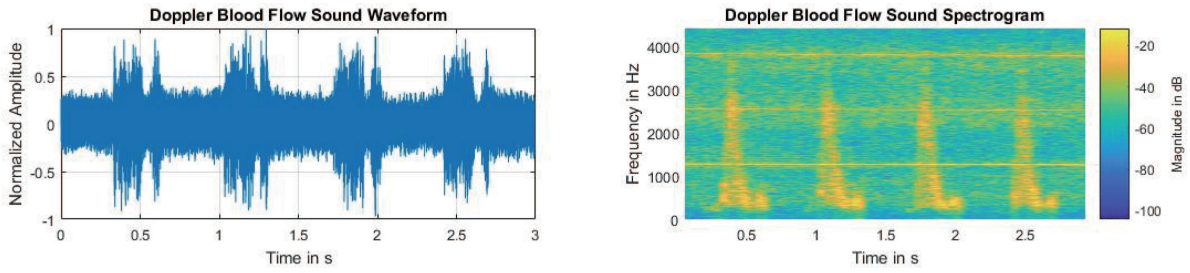


Figure 2. (color online) Sample graphical representation of Doppler blood flow sounds in the time- and time-frequency domains

For practical reasons, audio recordings were taken from the wrist skin surface instead of anal canal. The proctoscope with an 8 MHz transducer was placed directly over the skin and gently moved around to obtain Doppler sounds. The digital audio recorder was used to receive and store the sounds produced by the Doppler processor speaker. These procedures were suggested and approved by the collaborating surgeon. Doppler sound samples were manually segmented to form 0.7 seconds signal for each sample. The final dataset included a total of 100 Doppler sounds consisting of three categories mentioned previously. From the available data, 30% were allocated for the test set while 70% data were partitioned into training and validation sets by using 5-fold cross validation.

The Doppler sound signals were downsampled to 8.82 kHz, after which they were filtered with a low-pass 5th-order Butterworth filter with a cut-off frequency of 1.5 kHz. Finally, the Doppler sound signals were normalized to a fixed amplitude of -1 to 1.

2.3. **MFCC-based signal representation.** The MFCC reflects the nonlinear correlation between human auditory perception and the frequency of the incoming sound as formulated in (1):

$$Mel(f) = 1127 \log_e \left(\frac{f}{700} + 1 \right) \tag{1}$$

where $Mel(f)$ is the frequency in Mel scale and f is the actual frequency of perceived sound. The MFCC feature extraction procedure consists of six steps: 1) pre-emphasis, 2) window framing, 3) discrete Fourier transform (DFT), 4) Mel-filtering, 5) logarithmic spectrum calculation, and 6) discrete cosine transform (DCT). Mel spectrum is obtained by passing the power spectrum through a series of Mel-scale triangular filter banks. Logarithmic operation is performed at each frame to obtain logarithm power spectrum $S[m]$. Finally, $S[m]$ is put through DCT to derive the MFCC coefficients $c[n]$ as shown in (2):

$$c[n] = \sum_{m=0}^{N-1} S[m] \cos \left(\frac{\pi n}{m} \left(m - \frac{1}{2} \right) \right), \quad n = 1, 2, \ldots, M \tag{2}$$

where m is the number of the filter banks and M is the total number of the filter banks.

In this study, the preemphasis coefficient was set to 0.97. Overlap sliding windows were applied to the segments of 0.7 s using window length of 25 ms and a step size of 10 ms. For sampling frequency of 8.82 kHz, there were 220 samples per frame. The filter-bank consists of 20 bandpass triangular filters with lower and upper frequency of 300 Hz and 8 kHz, respectively. DCT, the final step of MFCC produced 13 coefficients. The energy of each coefficient array was then obtained by calculating its variance which can be expressed by (3):

$$\sigma = \frac{1}{m} \sum_{i=0}^{m-1} (x_i - \mu)^2 \tag{3}$$

Figure 3 shows a 0.7 s sample from the original one-dimensional (1D) arterial Doppler sound and the heatmap resulting from the MFCC conversion. The heatmap has a total of 60 rows and 13 columns.

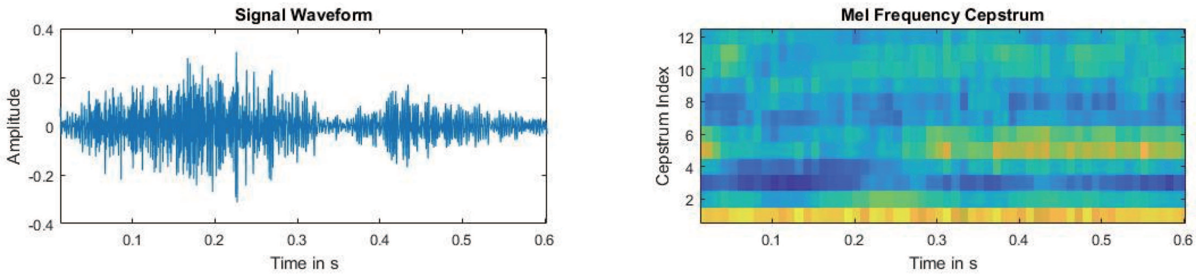


FIGURE 3. (color online) Doppler arterial sound in the time domain and its MFCC representation

2.4. **SVM classification model.** The SVM classifier splits up training data points $D = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$ into two groups separated by a gap called hyperplane. In this study, one group is arterial sound in contrast with non-arterial sound on the other side. Basically, SVM is a supervised machine learning method that aims to solve the binary classification problem by designating an optimal hyperplane formulated as follows (4):

$$H(x) : w \cdot x - b = 0 \tag{4}$$

in which two classes are separately labeled as $y_i \in \{-1, +1\}$. Hyperplane $H(x)$ is found by deciding two hyperplanes in parallel H_1, H_2 that have maximum margin of $2/\|w\|$ without any data points between them. Maximizing margin means making the $\|w\|^2$ value the minimum value. This optimization problem can be considered as a convex quadratic problem in (w, b) in a convex set which can be expressed as in (5):

$$\frac{\min}{wb\varepsilon} J(w, e) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \varepsilon_i \tag{5}$$
$$\text{s.t. } y_i \left[w^T \varphi(D_i) + b\right] \geq 1 - \varepsilon_i,\ \varepsilon_i \geq 0,\ i = 1, \ldots, n$$

where ε_i and C are flexibility variables and penalty parameters, respectively. C is an important parameter in SVM to control approximation errors, in which a large value of C leads to a narrow margin and vice versa. There are several selections for SVM kernel functions, such as linear, polynomial, and Gaussian RBF kernels. When using nonlinear kernels, SVM requires the optimization of another parameter gamma (γ), to achieve better outcomes. The γ parameter defines the curvature of the decision boundary, such that a small value of γ creates a broad decision region and vice versa. In general, lower values of C and higher values of γ mean more accuracy. Typical values for C are $0.1 < C < 100$ while those for γ are $0.0001 < \gamma < 10$. However, specific optimal values are particular to the dataset characteristics and the classification problem that is solved. In the present study, polynomial and Gaussian kernel functions were examined. Gamma value was varied from 1 to 6 and the C value was set to 50.

3. **Results and Discussions.** Experiments were carried through in this section to evaluate the performance of the proposed algorithm for arterial Doppler blood flow sound detection. The feature extraction process based on the MFCC was assembled with the SVM model to build a classification system. Optimal setups for acoustic features and SVM structures were investigated in the experiments. For comparison, NB classifier was also implemented and tested. In classification problems, accuracy is generally used as an evaluation metric. This measurement can be defined as in (6):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

The MFCC-based feature extraction was used to obtain the acoustic features from the Doppler blood flow sound signals. Applying this process to each sample resulted in 2D matrix with the size of 13 columns $\times$ 60 rows representing the MFCC coefficients and feature vectors, respectively. The variance was taken from individual coefficient arrays to form 13 statistical features for each sample. An example of three categories with 13 statistical features can be seen in Table 1.

Table 1. Example of datasets constructed from the variance of MFCC coefficient arrays

MFCC coefficient No.	Doppler arterial sound sample	Doppler venous sound sample	Doppler rubbing sound sample
1	16.86	2.61	8.57
2	7.22	8.04	19.24
3	13.23	2.62	15.14
4	26.40	7.85	75.69
5	37.14	6.85	8.42
6	43.89	5.17	7.83
7	24.47	6.18	12.93
8	7.15	11.75	33.56
9	13.30	9.20	20.06
10	7.40	5.45	10.05
11	7.28	7.57	11.37
12	11.66	5.58	8.59
13	6.61	5.75	4.68

Variance can be described as the averaged power of a signal's random deviations. From Figure 4, it can be noted that the coefficients of the Doppler venous sound have the lowest power among other categories. The signal power distribution of Doppler arterial sounds is mainly concentrated on MFCC4, MFCC5, and MFCC6. Furthermore, the coefficient power of the Doppler rubbing sounds coefficients power is mostly uniform except for the sharp peak in MFCC4.

A pair of MFCC coefficient resulting from the feature extraction process was then used as input of SVM classifier. Here, a feature selection algorithm is required to search for a subset of predictor variables that can optimally model the measured responses. Using excessive amounts of features may degrade prediction performance, even if most of the features are relevant. Several promising combinations of MFCC coefficients based on feature selection process were investigated as inputs of the SVM classifier. During the experiments, polynomial and Gaussian kernel functions were tried as possible solutions. The accuracies of the SVM classifiers with varied kernel functions and parameters for MFCC1 and MFCC3 as classifier inputs are illustrated in Figure 5(a). Furthermore, an NB classifier was developed for comparison. SVM and NB are two classifiers with different approaches, one is geometric in nature while the other is probabilistic. The comparison result is depicted in Figure 5(b). Next, the inputs of classifiers were changed to MFCC3 and MFCC13, and the performance curve can be observed in Figure 6(a) and Figure 6(b), respectively. The final input combination is MFCC5 and MFCC10, the classification accuracy of which is presented in Figure 7(a) and Figure 7(b).

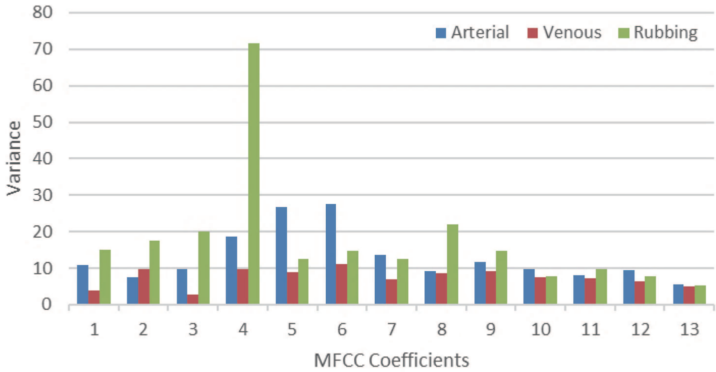
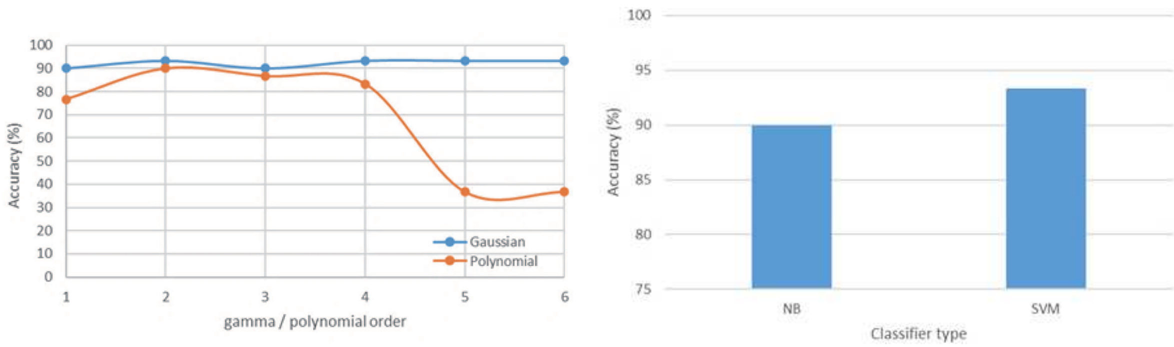
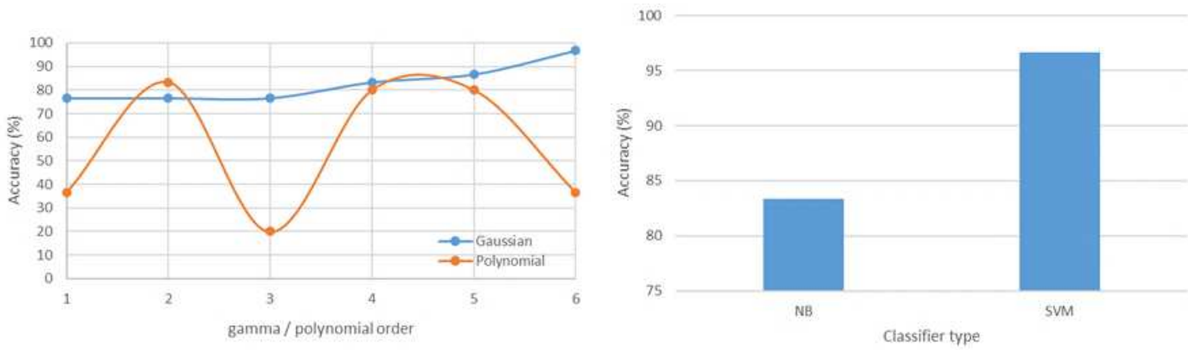


FIGURE 4. The variance of all MFCC coefficients for three Doppler sound categories



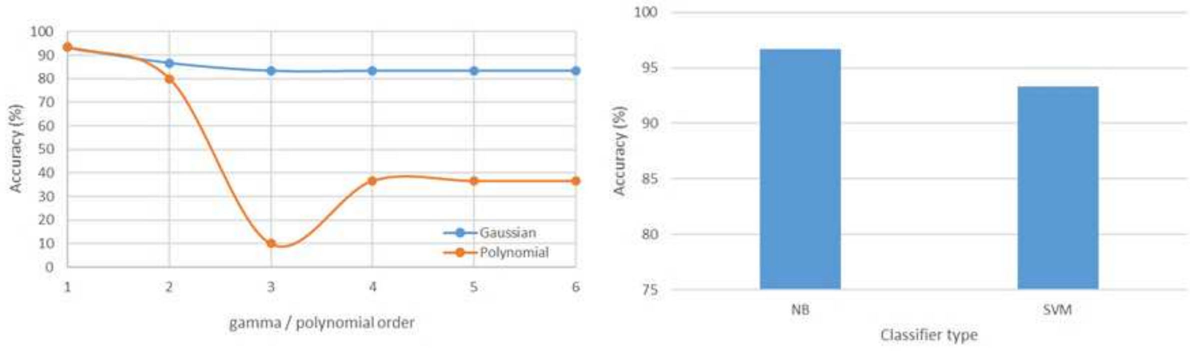
(a) (b)

FIGURE 5. (a) Accuracy dependence on the kernel functions and their parameters when the MFCC1 and MFCC3 are used as inputs to SVM classifier; (b) performance of the alternative classification method compared to the SVM classifier



(a) (b)

FIGURE 6. (a) Accuracy dependence on the kernel functions and their parameters when the MFCC3 and MFCC13 are used as inputs to SVM classifier; (b) performance of the alternative classification method compared to the SVM classifier



(a) (b)

FIGURE 7. (a) Accuracy dependence on the kernel functions and their parameters when MFCC5 and MFCC10 are used as input to the SVM classifier; (b) performance of the alternative classification method compared to the SVM classifier

The comparative simulation results of the three input combinations to SVM under different parameters indicate that the Gaussian kernel consistently yields the largest accuracy. For instance, in the MFCC1 and MFCC3 input combination with γ value and polynomial order 1, Gaussian kernel shows 90% accuracy, whereas polynomial kernel has 76.66% accuracy. Gaussian kernel also exhibits more coherent accuracy over various kernel parameters compared to the polynomial counterpart. The best classification accuracy of 96.66% is achieved when using the MFCC3 and MFCC13 input configuration and Gaussian kernel with γ value of 6. Furthermore, the performance of NB as alternative classifier is mostly lower than the best SVM classifier, except for the MFCC5 and MFCC10 input combination. As it can be seen from Figure 5(a), Figure 6(a), and Figure 7(a), γ parameter plays a critical role in determining classification performance and therefore γ is considered important for the calculation of SVM model. The proposed method achieves better performance compared to the pioneering investigation [27] and previous studies which investigated cardiac Doppler sounds based on similar SVM classifiers [12,13]. However, they used a larger sample size, that is 215 compared to 100 samples in this study.

4. **Conclusions.** In this paper, the MFCC feature extraction scheme is presented to characterize the acoustic properties of Doppler sounds. The SVM-based method is proposed for feature learning and classification. Based on simulation results, only the selected MFCC coefficients (i.e., MFCC1, MFCC3, MFCC5, MFCC10, and MFCC13) are suitable for representing the Doppler blood flow sound characteristics. Furthermore, the Gaussian kernel yields more stable accuracy over varying parameters compared to the polynomial kernel. In classifying Doppler blood flow sound, SVM generally performs better than NB. The results also reveal that, by using MFCC3 and MFCC13 as SVM inputs, the arterial Doppler blood flow sound can be effectively recognized among 100 sound samples with 96.66% accuracy. Future research work should aim to reproduce the results using a larger database. Also, further research is recommended for the exploration of more representative feature extraction strategies based on application specific MFCC.

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