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Class Determination Based on Kullback-Leibler Distance in Heart Sound Classification

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Abstract

Stethoscopic auscultation is still one of the primary tools for the diagnosis of heart diseases due to its easy accessibility and relatively low cost. It is, however, a difficult skill to acquire. Many research efforts have been done on the automatic classification of heart sound signals to support clinicians in heart sound diagnosis. Recently, hidden Markov models (HMMs) have been used quite successfully in the automatic classification of the heart sound signal. However, in the classification using HMMs, there are so many heart sound signal types that it is not reasonable to assign a new class to each of them. In this paper, rather than constructing an HMM for each signal type, we propose to build an HMM for a set of acoustically-similar signal types. To define the classes, we use the KL (Kullback-Leibler) distance between different signal types to determine if they should belong to the same class. From the classification experiments on the heart sound data consisting of 25 different types of signals, the proposed method proved to be quite efficient in determining the optimal set of classes. Also we found that the class determination approach produced better results than the heuristic class assignment method.

Keywords: *Hidden Markov Model, Heart sound classification, Class Determination, Kullback-Leibler Distance*

I. Introduction

Heart auscultation is important in the diagnosis of heart diseases. Although there are some advanced techniques such as the echocardiography and the MRI, it is still widely used in the diagnosis of the heart disease because of its relatively low cost and easy accessibility. However, detecting symptoms and making diagnosis from hearing the heart sound require a skill that takes years of experience in the field.

A machine-aided diagnosis system for the heart sound signal would be very useful for assisting the clinicians to make better diagnosis of the heart disease. With the recent developments of the digital signal processing techniques, artificial neural networks (ANNs) have been widely used as the automatic classification method for the heart sound signals [1-5]. Recently, the HMM has also shown to be very effective in modeling the heart sound signal [6-7]. The highly dynamic and non-stationary nature of the heart sound signal makes it appropriate to model the signal with the HMM. In a recent study [8], they found that the HMM works much better than the ANN in classifying the heart sound signals corresponding to 10 different kinds of heart diseases. The superior performance of the HMM may come from its proven excellence in modeling non-stationary time- sequential input patterns compared with the ANN.

There are many different heart sound signal types which are characterized by their unique signal shapes and spectral characteristics. Although the signal

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types are mainly affected by the kind of heart diseases, we can easily find cases where quite different signal types are generated from the same heart disease. From this relationship between the heart sound signal types and the heart diseases, there is the problem of class determination in classifying the heart sound signals using HMMs. In a simple thought, one may assign a class to each type of heart sound signals. However, such an assignment will increase the number of classes indefinitely as there are too many signal types. And such a large number of classes will increase the confusability between classes and consequently result in poor classification accuracy. Also one may consider to assign the various signal types from the same heart disease to a class. However, such an approach will reduce the discrimination between classes due to poor modeling.

Although it is assumed that the general type of the heart sound signal consists of 4 components, namely, S1, systole, S2 and diastole, there are many variations in the characteristics of the heart sound signal that result in a number of signal types. The kind of the heart diseases mainly determines the signal type. However, various factors such as the severeness of the diseases, the conditions of the patient and the locations of the signal measurement also contribute to determine the type of the signal. And the signal types are distinguished from each other by the severeness of the murmurs and clicks that exist in the systole and diastole regions of the heart sound signal.

Instead of assigning a new class to each type of the heart sound signal, we propose to assign a class for a set of signal types that are acoustically-similar. In this manner, we reduce the number of classifiers that need to be constructed. Further, using this approach it is possible to determine if any unseen type of signal to appear later will be assigned to the existing class or to a new class. To define the classes for the signal types, we use the KL (Kullback-Leibler) distance between different signal types to determine if they should belong to the same class.

In the next section, we will explain the method how to construct classifiers using HMMs and in section 3, the proposed method of determining classes based on KL distances is explained. In section 4, we show experimental results which demonstrate the feasibility of the proposed method and finally, we make conclusion in section 5.

II. Methods

2.1. Classification of Heart Sound Signals using HMMs

The HMM has proven to be efficient in recognizing non-stationary time sequential patterns like speech. As the heart sound signal is similar to the speech in that its statistical characteristic is non-stationary, the modeling of the heart sound signal with the HMM will be feasible. The types of the HMM depend on its structure. In the speech recognition, the speech signal is usually modeled by the left-to-right HMM in which the state transitions are allowed only from left to right including self-transitions. This is quite reasonable because the left-to-right HMM can model signals whose properties change with time in a sequential manner. In this viewpoint, we think that the heart sound signal also can be modeled by the left-to-right HMM. A four state left-to-right HMM for a cycle of the heart sound signal is shown in Fig. 1 in line with the four components of the heart sound signal, namely S1, systole, S2 and diastole [7-8]. The number of states in the HMM is usually determined based on the nature of the signal being modeled. Each state of the HMM in Fig. 1 is assigned to a component of the heart sound signal because the signal characteristics in each component may be thought to be homogeneous. In [8], they found that the 4-state left-to-right HMM was sufficient to model a cycle of the heart sound signal. The spectral variability in each state is modeled using multiple mixtures of multivariate Gaussian distributions. Given the observation $y(t)$, the output probability distribution in the state j is given

$$b_j(y(t)) = \sum_{m=1}^{M} c_{jm} N(y(t), \mu_{jm}, \Sigma_{jm}) \quad j = 1, \cdots N \tag{1}$$

where $N(y(t), \mu_{jm}, \Sigma_{jm})$ is a multivariate Gaussian distribution, with mean vector μ_{jm} and covariance matrix Σ_{jm}, each mixture component having an associated weight c_{jm}. M is the number of mixture components in each state. Also, the transition from the state i to j is controlled by the transition probability as follows.

$$a_{ij} = P(j|i) \tag{2}$$

In Fig. 2, we show the procedure of classifying the heart sound signal using the trained HMMs. An HMM is constructed for each class of the heart sound signal using the training data corresponding to the class. The HMM parameters are estimated during

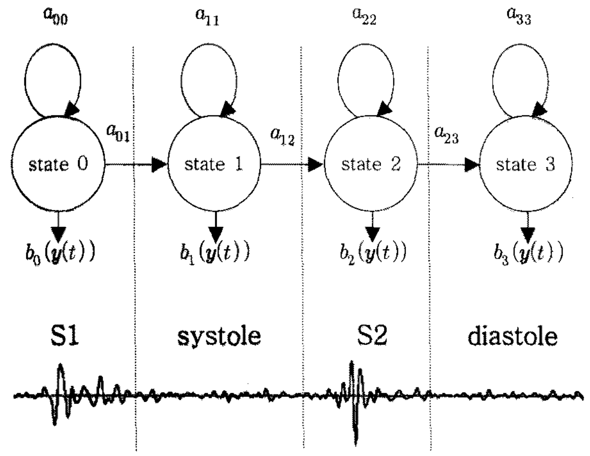


Fig. 1. A left-to-right type HMM for a cycle of the heart sound signal.

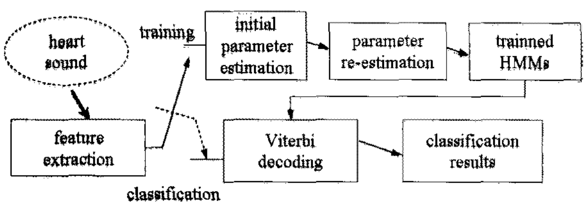


Fig. 2. The procedure of classifying the input heart sound signal using the trained HMMs.

the training procedure. For the initial parameter estimation, every cycle of the heart sound signal is manually segmented into 4 regions giving the statistical information corresponding to each element [7]. And the initial HMM parameters are re-estimated using the Baum-Welch algorithm for the maximum likelihood (ML) parameter estimation until some convergence criterion is satisfied. In classification, the Viterbi decoding is applied to find the class (HMM) which gives the best likelihood score among the trained HMMs given the input heart sound signal. The feature vectors used are 18-th order mel-frequency filter bank outputs derived from the fast Fourier transform (FFT).

2.2. Determining the Classes

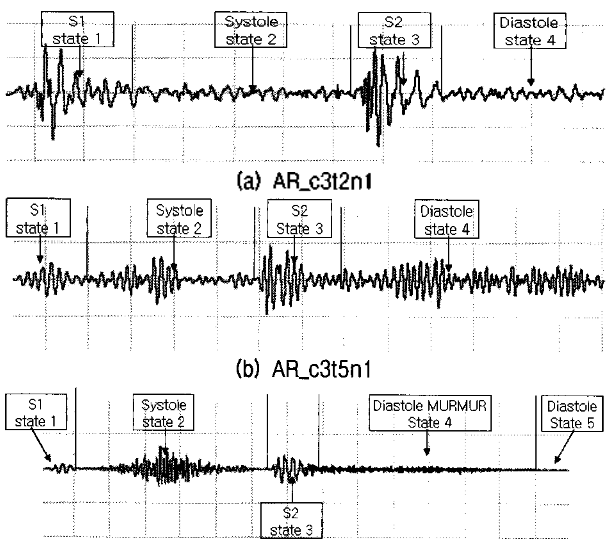
Heart sound signals have various signal types depending on the cause of the signal generation. Mainly, the kind of the heart disease associated with the heart sound determines the signal type. However, various other factors such as the severance of the diseases, the conditions of the patient and the locations of the signal measurement also contribute to determine the type of the signal. The differences between the signal types are observed in the magnitude and locations of the murmurs and clicks that usually exist in the systole and diastole regions of the heart sound signal. As there are so many signal types in the heart sound, it is not reasonable to assign a new class for each of the signal types. Such an assignment of classes will result in insufficient training of the HMM parameters and increase the confusability between classes and consequently, may lead to lower classification accuracy.

In this paper, we used 25 types of heart sound signals as shown in Table 1. The names of the signal types and the numbers of the data are also shown. The front part on the name represents the kind of disease associated with the signal type. As shown in the table, there may be several signal types from the same kind of heart disease. For example, AR_c3t2n1, AR_c3t5n1 and AR_c3t7n1 all correspond to the same kind of disease (AR). In Fig. 3, we show examples of the heart sound signal types related with the AR. As shown in the figure, the signal types show quite different characteristics although they come from the same kind of disease. From this fact, we can see that it is not reasonable to assign the signal types to the same class just because they come from the same disease. Some method to determine the optimal set of classes will be necessary.

There are totally 9 kinds of heart diseases associated with the signal types used in this paper: NS (normal sound), IM (innocent murmur), AR (Aortic Regurgitation), AS (Aortic Stenosis), CA (Coarctation of the Aorta), MR (Mitral Regurgitation), MS (Mitral Stenosis), MVP (Mitral Valve Prolapse) and TR (Tricuspid Regurgitation). In the proposed method of determining the classes, we consider all the signal types associated with the same disease as the candidates to form the same class. Signal types from other kinds of diseases are excluded from the candidates, because the main objective of the classification is to recognize the kind of diseases of the input heart sound signal.

Table 1. The various types of heart sound signals and their associated heart diseases in the classification experiment.

Kind of Diseases	Name of Signal Types	Number of Data	Kind of Diseases	Name of Signal Types	Number of Data
NS	NS	15	MR	MR_hsmur	13
IM	IM_2lis	14		MR_absent	18
	IM_4lis	14		MR_mdmur	11
AR	AR_c3t2n1	21	MS	MS_presys	20
	AR_c3t3n1	16		MS_af	19
	AR_c3t5n1	15		MS_rapid	12
	AR_c3t7n1	16		MS_ph	12
AS	AS_msmur	25	MVP	MVP_lsmur	20
	AS_apex	19		MVP_msc	15
	AS_ar	20		MVP_multi	15
	AS_prebeat	10	TR	TR_hsmur	17
	AS_cbar	15		TR_ph	42
CA	CA	20			



(a) AR_c3t2n1

(b) AR_c3t5n1

(c) AR_c3t7n1

Fig. 3. Examples of the heart sound signal types related with the AR.

The class determination process proceeds as follows. We first consider an initial signal type T1 and a second type T2 from the same kind of heart disease. Our objective is to determine if the signal type T1 and T2 should be assigned as members of the same class. To determine the similarity of the signal type T1 and T2, we utilize the Kullback–Leibler (KL) distance. If we assume that output probability distribution for each state of the HMM is a single mixture Gaussian and $\mu_{j,T1}$, $\mu_{j,T2}$, $\Sigma_{j,T1}$, $\Sigma_{j,T2}$ are the N dimensional mean vectors and diagonal covariance matrices for the state j of the HMMs corresponding to T1 and T2 respectively, then we can compute the KL distance between T1 and T2 for the state j as [9]

$$D_j(T1,T2) = \frac{1}{2}\sum_{i=1}^{N}\left[\log\left(\frac{(\Sigma_{j,T1})_{ii}}{(\Sigma_{j,T2})_{ii}}\right) + \frac{((\mu_{j,T2})_i - (\mu_{j,T1})_i)^2}{(\Sigma_{j,T1})_{ii}} + \left(\frac{(\Sigma_{j,T2})_{ii}}{(\Sigma_{j,T1})_{ii}} - 1\right)\right],$$
$$j = 1,2,3,4$$

Signal types T1 and T2 are deemed associated with the same class if $\min\{D_j(T1,T2), D_j(T2,T1)\} < T$ for all states j. There is flexibility in the choice of the threshold T. The smaller T, the more closely related are the signal types in a given class. However, if T is made too small, the number of classes proliferates.

In the same manner as above, all the signal type pairs within the same disease are checked if they can be clustered into the same class. If any signal type is not close to any other signal types within the same disease, it is solely assigned to a distinct class.

Once the classes consisting of a set of signal types which are acoustically similar are determined in the proposed algorithm, the HMM for each class is re-estimated using all the training data corresponding to the class. In the next section, we show some experimental results showing the effectiveness of the proposed method in the class determination.

III. Feasibility Tests and Discussion

The heart sounds for the feasibility test experiments were taken from the clinical training audio CDs for the physicians [10]. The original data were down sampled to 16 KHz and stored in a 16 bit resolution. The classification tests were performed with 434 heart sounds representing 25 different signal types. Each heart sound data consists of one cycle of the heart sound signal which is obtained by manually segmenting the original continuous heart sound signal. The signal types and their associated diseases were shown in Table 1. Initially an HMM was constructed during training for each type of the heart sound signal using the corresponding data. A single Gaussian mixture output distribution for each of a 4 state left-to-right HMM (Fig. 1) was used to model the heart sound signal. To overcome the problem of small amount of data collected, the classification test was done by the Jack-Knifing method. In this process, the HMM was trained with all the data available except the one used for testing. The process was repeated so that all the data can be used for testing. The tested results were then averaged to give the classification accuracy rate. The heart sound signal was processed on a frame by frame basis in the HMM. The length of a cycle in the signal ranged from 500 ms to 1000 ms and we set the frame rate and length to be 2.5 ms and 7.5 ms, respectively.

Table 2 shows the class determined by the proposed method as the threshold T of the KL distance varies. If we assume $T=0$, every signal type constitutes a distinct class resulting in 25 classes. As shown in the table, as we increase T to 100, the number of classes dropped to 15. If $T=\infty$, the number of classes will be 9 equal to the number of heart diseases listed in the first column of the table. The bar (–) sign in the table means that the classes in the left column have been merged into the same class although the name of the new class is not given for notational simplicity. For example, the signal type IM_2lis and IM_4lis which constitute separate classes when $T=0$ are merged together to form a new class when $T=30, 50, 100$.

Fig. 4 also shows the classification accuracy as the threshold T varies. When all the signal types from the same heart diseases are assigned to the same class by letting $T=\infty$, the classification accuracy is very low. This means that the various types of signals from the same heart disease differ too much in their characteristics to be included in the same

Table 2. Classes determined as the threshold T of the KL distance is varied.

9 kinds of diseases	25 classes (T = 0)	19 classes (T=30)	18 classes (T=50)	15 classes (T=100)
NS	NS	NS	NS	NS
IM	IM_2lis	–	–	–
	IM_4lis			
AR	AR_c3t2n1	AR_c3t2n1	AR_c3t2n1	–
	AR_c3t5n1	AR_c3t5n1	AR_c3t5n1	
	AR_c3t7n1	AR_c3t7n1	AR_c3t7n1	
	AR_c3t3n1	AR_c3t3n1	AR_c3t3n1	AR_c3t3n1
AS	AS_prebeat	–	–	–
	AS_apex			
	AS_ar	AS_ar		
	AS_murmur	AS_murmur	AS_murmur	
	AS_cbar	AS_cbar	AS_cbar	AS_cbar
CA	CA	CA	CA	CA
MR	MR_hsmur	MR_hsmur	MR_hsmur	MR_hsmur
	MR_absent	–	–	–
	MR_mdmur			
MS	MS_presys	–	–	–
	MS_af			
	MS_rapid	–	–	–
	MS_ph			
MVP	MVP_lsmur	MVP_lsmur	MVP_lsmur	MVP_lsmur
	MVP_msc	–	–	–
	MVP_multi			
TR	TR_hsmur	TR_hsmur	TR_hsmur	TR_hsmur
	TR_ph	TR_hsmur	TR_hsmur	TR_hsmur

class. The HMMs for the classes will not be modeled sharply enough to distinguish one from another. The performance was found to be unsatisfactory when every signal type had its own distinct class (25 classes) at $T=0$, because the perplexity of classification was high. The highest classification accuracy was achieved when the number of classes is 19 with $T=30$. Fig. 4 shows that the optimal set of classes can be determined by setting an appropriate threshold value T. We also compared the proposed method with a heuristic method in which the set of classes is determined based on the observed similarity in the shapes of the signal waveform. The heuristic method produced 21 classes. We can see that the proposed method works better than the heuristic method when $T=30$ although a slight performance degradation was observed when $T=50$. Despite some perturbation in performance with T, the proposed method is advantageous since it is based on the objective criterion of the KL distance proven to be efficient in measuring the similarity between two statistical models. In contrast, the heuristic method is subjective and may show large variability in classification depending on the signal types.

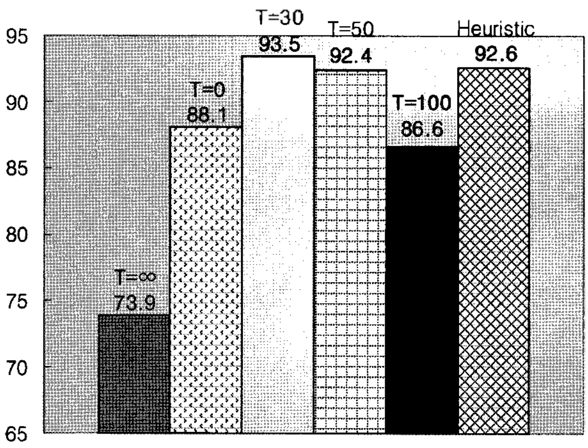


Fig. 4. Classification accuracy as the threshold T is varied.

Table 3. The classification results with respect to the 9 classes as the threshold value T is varied.

Number of classes	Classification accuracy(%)
25(T=0)	93.10
19(T=30)	94.23
18(T=50)	93.09
15(T=100)	87.56
9(T=infinity)	73.96
21(Heuristic)	93.55

The results in Fig. 4 do not necessarily mean that the we can obtain the same results when the classification is done with respect to the 9 kinds of heart diseases. In Table 3, we show the classification results as the threshold value T varies. The difference in the classification rates as the threshold changes is small compared with the results in Fig. 4. The performance improvement by the proposed method is not as significant as in Fig. 4. But this is expected as the aim of the class determination is not to achieve the best classification accuracy for the heart diseases. However, if the heart sound data used in the experiments are increased, the signal types from the same disease will be very various and the separate modeling of each signal type will show some performance limitation compared with the proposed signal type clustering approach. Also, the optimal set of classes found in the proposed method can be used to decide if any unseen type of signal to appear later will be assigned to an existing class or to a new class based on the KL distance.

IV. Conclusions

In this paper, we have proposed a method to determine the optimal set of classes in the heart sound signal classification. As there are many types of signals even from the same kind of heart diseases, it is necessary to cluster the various signal types into classes according to their similarity rather than assigning a separate class to each type of the signals. As we employ HMMs to model the heart sound signals, the KL distance which has shown to be efficient in measuring the similarity between statistical models was utilized to determine if the signal types from the same heart disease should be clustered into the same class. From the experimental results, we could see that the proposed method improved classification accuracy remarkably compared with the case when we assign a distinct class to each signal type and it also works better than the case when all the signal types in the same kind of diseases are assigned to a class. In addition, the proposed method is advantageous because it performs well compared with the heuristic method without the need to be subjective in determining the classes.

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