A multichannel decision-level fusion method for T wave alternans detection

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(Received 7 April 2017; accepted 22 July 2017; published online 6 September 2017)

Sudden cardiac death (SCD) is one of the most prominent causes of death among patients with cardiac diseases. Since ventricular arrhythmia is the main cause of SCD and it can be predicted by T wave alternans (TWA), the detection of TWA in the body-surface electrocardiograph (ECG) plays an important role in the prevention of SCD. But due to the multi-source nature of TWA, the nonlinear propagation through thorax, and the effects of the strong noises, the information from different channels is uncertain and competitive with each other. As a result, the single-channel decision is one-sided while the multichannel decision is difficult to reach a consensus on. In this paper, a novel multichannel decision-level fusion method based on the Dezert-Smarandache Theory is proposed to address this issue. Due to the redistribution mechanism for highly competitive information, higher detection accuracy and robustness are achieved. It also shows promise to low-cost instruments and portable applications by reducing demands for the synchronous sampling. Experiments on the real records from the Physikalisch-Technische Bundesanstalt diagnostic ECG database indicate that the performance of the proposed method improves by 12%–20% compared with the one-dimensional decision method based on the periodic component analysis. *Published by AIP Publishing.* [http://dx.doi.org/10.1063/1.4997267]

I. INTRODUCTION

Sudden cardiac death (SCD) is known for its suddenness and high mortality rate.[1,2] Some researches show that in developed countries, 1 out of 1000 subjects die every year due to SCD, which is almost 20% of all deaths.[3,4] According to the statistical results from the American Heart Association, the survival rate of the out-of-hospital cardiac arrests is only 5%.[5] Unless cardiopulmonary resuscitation is performed within several minutes after the cardiac arrest, the chance of survival would be very slim.[6] Along with its sudden onset and rapid development, the risk stratification and accurate prediction are especially important for preventing SCD.

The cause of most SCDs is the ventricular arrhythmia, which can be predicted by T wave alternans (TWA) in the body-surface electrocardiogram (ECG).[7,8] The progressive increase of TWA preceding the onset of spontaneous ventricular arrhythmias has been revealed by many clinical studies.[9,10] It has been demonstrated that TWA is one of the most promising SCD predictors.[11,12] As a cardiac phenomenon, TWA refers to a periodic beat-to-beat alternating change in the amplitude or shape of the ST-T complex in the body-surface ECG (see Fig. 1). Technically, TWA is at the level of several micro-volts, which is hard to discover by the naked eye. In order to detect TWA as accurate as possible, instruments with custom-designed signal processing methods are needed.

One of the greatest challenges for the TWA detection is the combination of uncertain and competitive information from different channels to make the final decision. TWA is a complex multi-source signal, which is usually caused by distributed myocardial damages and arrhythmic complications. It suggests that the information from a single channel is one-sided and one-dimensional, so all the information from different channels should be combined to make the final decision. But the TWA in the body-surface ECG has inevitably been distorted during the nonlinear propagation from cardiac myocytes to the body surface. Along with the effects of the strong noises, the information from different channels is uncertain and competitive with each other.

To reach a consensus on the final decision, most existing methods just get rid of partial information to reduce conflict. For most single-channel methods, a fixed channel is used while the information in other channels is discarded. A multichannel hard-decision strategy called "OR" is to choose one channel, which is supposed to have a higher detection accuracy than others, to make the final decision. But in essence, only partial information from a certain channel is utilized. For most multichannel methods, the information is fully used in the TWA estimation by linear transformation while the "OR" strategy is performed in the decision process. Considering the multi-dimensional nature of TWA, these methods based on the one-dimensional signal make the final decision with a relatively low information utilization rate.

To address the challenge, a new decision-level fusion method based on the Dezert-Smarandache Theory (DSmT) is proposed in this paper. The DSmT is a promising information fusion theory that derived from the classic Dempster-Shafer theory.[13] More reasonable and accurate final decisions can be made by taking advantage of the ability of the DSmT to combine the uncertain and even conflicting information with decision-making supports. Different from getting rid of highly competitive information, it utilizes this information by

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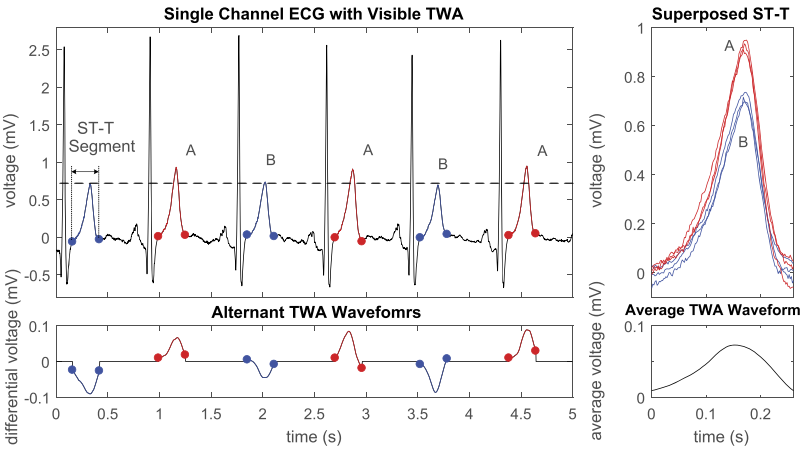

FIG. 1. The phenomenon of TWA. (a) Single channel ECG with visible TWA (top) and alternant TWA after removing average ECG waveform (bottom). (b) Superposition of ST-T segments (top) and average TWA waveform (bottom). The beat-to-beat alternating shapes of ST-T segments are defined as TWA. The average waveform between A and B is the average TWA waveform. (It is worth noting that the TWA shown in this figure is much larger than usual for convenience purpose.)

a redistribution process in the decision-level fusion. The main contribution of this study is to improve the information utilization rate to make a more reasonable decision. Due to the channel-by-channel design, it also provides a possibility of extending the multichannel TWA detection to low-cost and portable applications.

II. RELATED WORK

In the last few decades, a number of methods and schemes were proposed to detect TWA. From single-channel to multichannel schemes, these methods would be introduced as follows.

Most single-channel methods roughly fall into three classes.[14] (1) The methods in the first class are based on the short-time Fourier transform. Most early methods, such as the spectral method,[15,16] the complex demodulation method,[17] the Poincaré map distance method,[18] the projection in 2-periodicity space method,[19] and Student's t-test method,[20] belong to this class. Although these methods have a high sensitivity, they usually require long data (about 128 beats), resulting in a low temporal resolution. Since the length of some transient TWA can reach as small as seven beats, the false negative rate of these methods is relatively high. (2) The methods from the second class are all based on the sign change counting method. This class includes the Rayleigh test method[20] and the correlation method.[21–23] These methods use a strategy based on the time-domain observation of the sign changes in a beat-to-beat series. Although these methods have increased the temporal resolution, they also become more sensitive to noises and increase the false alarm rate. (3) The methods from the third class are nonlinear filtering methods. Two representative methods of this class are the modified moving average method[24] and the Laplacian likelihood ratio (LLR) method.[14,25,26] They utilize various nonlinear filters to identify and remove outliers in signal. This enables them to partially eliminate noises and usually have better performance in the simulation study. But since most nonlinear criteria are designed arbitrarily, the performance of these methods varies for different instruments and different clinical settings. Some other methods that combine these single-channel methods with the decomposition algorithm such as wavelet[27,28] and empirical mode decomposition[29,30] were also proposed. For all the three kinds of methods, a more important limitation is their single-channel frame. Since the information from a single channel is one-sided and one-dimensional, these single-channel methods always have a relatively low detection accuracy and less robust detection performance. To make the final decision in a more comprehensive way, multichannel schemes are needed.

Several multichannel schemes[31] were proposed in recent years. They utilize blind source separation techniques, such as the principal component analysis (PCA)[32,33] and the periodic component analysis (πCA),[34] to concentrate the TWA information into one or several dimensions (or components). Some methods use tensor to explore the relationship between beats and channels.[35,36] After the linear transformation, the consistent information is mainly concentrated into the same dimension while highly competitive information is mainly transformed into different ones. This kind of method actually shows substantial improvement of detection accuracy in simulation studies.[31] But in the final decision process, most of them adopt a one-dimensional decision method called "OR." This decision method just chooses the single channel or dimension with the maximum detection statistic to make the final decision. So the competitive information is still discarded to reach a consensus on the final decision. Besides, the linear transformation will inevitably introduce errors, which will be further delivered to the decision process. So they may even make themselves less robust, especially when the alternans-to-noise rate (ANR) is low. In order to utilize the competitive information from different channels or dimensions in a more reasonable and comprehensive way, new multichannel decision methods are needed.

III. METHOD

The general block diagram of the proposed multichannel decision-level fusion method is shown in Fig. 2. It consists of four stages: the signal preprocessing, the characteristic parameter extraction, the decision-level fusion, and the decision making.

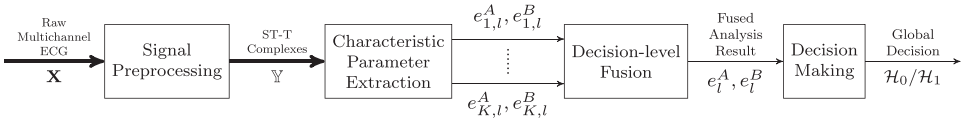

FIG. 2. General block diagram of the proposed decision-level fusion method (multi-DSmT). The bold lines indicate that their corresponding data flows consist of data from multiple channels.

A. Signal preprocessing

Before the detection, ST-T complexes should be extracted from the raw multichannel ECG during the signal preprocessing stage. As summarized in Ref. 14, four steps would be taken in this stage. They are the linear filtering, the baseline cancellation, the ST-T segmentation, and the data reduction.

Linear filters would be applied to the raw multichannel ECG $\mathbf{X}$ to reject out-of-band noises. A low-pass filter with a 100 Hz cutoff frequency and a notch filter with a 50/60 Hz center frequency are used in this scheme. The baseline wander is then removed with a cubic spline interpolation technique.[37]

The ST-T segmentation is conducted in three steps. First, all beats are aligned by R peaks and their multichannel average waveform is obtained. Second, a multichannel delineation algorithm based on ECG slope criteria[38,39] would be applied to determine the limits of the ST-T complex based on the average beat waveform. Finally, the corresponding segments in each beats are extracted and put together into a $N \times M \times K$ ST-T tensor $\mathbb{X}$, where N is the number of samples of the ST-T segment, M is the number of beats, and K is the number of channels. It is worth noting that for certain ECG record, the length of the ST-T segment is fixed and determined by the delineation algorithm. For different ECG records, the length of the ST-T segment may be totally different.

Besides, to reduce the number of samples to be processed while preserving information about TWA, the data reduction would be done by a decimation process. Since the TWA waveform is mostly concentrated between 0.3 Hz and 15 Hz,[40] the sampling frequency of the decimated signal should be above 30 Hz. In this method, each model-1 fiber $\mathbf{x}_{:mk}$ (ST-T complex) of $\mathbb{X}$ whose sampling frequency is 1 kHz would be decimated by a factor of $Q = 32$, which makes the sampling frequency of the output signal to be 31.25 Hz. The output of the data reduction can be marked as $P \times M \times K$ tensor $\mathbb{Y}$ where $P = \lfloor N/Q \rfloor$. The element $y_{p,m,k}$ of $\mathbb{Y}$ indicates the pth sample of the mth ST-T complex from the kth channel.

B. Characteristic parameter extraction

Before fusion, the relevant characteristic parameters for each channel would be extracted first. In this method, the estimations of average energy of TWA and the noises in each channel are calculated.

Due to the transient, non-stationary nature of TWA, each detection must involve a limited set of neighbor beats. So a beat-by-beat sliding window analysis strategy[14] is used. By applying this strategy, $L = \lfloor (M - J)/D \rfloor + 1$ analysis windows will be constructed, where M is the number of beats that are located in the waveform delineation, J is the analysis window length, and D is the shift parameter. The lth analysis window will contain W consecutive beats that are started from the $[(l-1) \times D + 1]^{th}$ beat. In this method, $J = 32$ and $D = 1$ are adopted and the corresponding number of the analysis window will be $L = M - 31$. It is worth noting that the highly overlapped analysis windows (small D) are usually used in the theoretical analysis and the simulation study to obtain a better representation of the TWA evolution at the cost of a larger amount of computation. In clinical applications, there will be a trade-off between the temporal resolution and the amount of computation, usually resulting in a much larger D. Accordingly, the 3-way ST-T tensor $\mathbb{Y}$ can be rearranged as a 4-way tensor $\mathbb{Z}$, whose size is $P \times J \times K \times L$ and its element $z_{p,j,k,l}$ indicates the pth sample of the jth ST-T complex in the kth channel from the lth analysis window.

The average energy of noises will be estimated after removing the background ECG and the potential TWA component. The background ECG can be removed by subtracting the average waveform as

$$z'_{p,j,k,l} = z_{p,j,k,l} - \frac{1}{J}\sum_{j=1}^{J} z_{p,j,k,l}. \tag{1}$$

The potential TWA component can be removed as

$$z''_{p,j,k,l} = z'_{p,j,k,l} - \hat{a}_{p,k,l} \cdot (-1)^j, \tag{2}$$

where

$$\hat{a}_{p,k,l} = median\left\{ z'_{p,j,k,l} \cdot (-1)^j |_{j=1}^{J} \right\} \tag{3}$$

is the estimation of the potential TWA waveform based on the model in Refs. 14, 25, and 26 with Laplacian noise. Then the energy of noises can be estimated as

$$e^{\mathrm{B}}_{k,l} = \frac{1}{JP}\sum_{j=1}^{J}\sum_{p=1}^{P}(z''_{p,j,k,l})^2. \tag{4}$$

As analyzed in Ref. 14, the energy at 0.5 cycles-per-beat (cpb) of the power spectrum of the beat-to-beat series $\mathbf{z}_{p:kl}$ from a certain channel and a certain analysis window is regarded as the mixture of TWA and noises. Its average value during the ST-T segment can be estimated as

$$e^{\mathrm{Mix}}_{k,l} = \frac{1}{JP}\sum_{p=1}^{P}\left[\sum_{j=1}^{J} z_{p,j,k,l} \cdot (-1)^j\right]^2. \tag{5}$$

Then the average energy of TWA for a certain channel and a certain analysis window can be calculated as

$$e^{\mathrm{A}}_{k,l} = \begin{cases} 0, & \text{for } e^{\mathrm{Mix}}_{k,l} \le e^{\mathrm{B}}_{k,l}, \quad (6a) \\ e^{\mathrm{Mix}}_{k,l} - e^{\mathrm{B}}_{k,l}, & \text{for } e^{\mathrm{Mix}}_{k,l} > e^{\mathrm{B}}_{k,l}. \quad (6b) \end{cases}$$

C. Decision-level fusion

After the channel-by-channel characteristic parameter extraction, a decision-level fusion method derived from the proportional conflict redistribution rule no. 6 (PCR6) from the DSmT[41] is performed to fuse this competitive information from different channels in a reasonable and comprehensive way.

Within the framework of the DSmT, three main steps, including the basic belief assignment (BBA) extraction, the fusion, and the probabilistic transformation, should be done for a complete DSmT fusion process. But in the TWA detection, since the format of the characteristic parameters has been unified and the final decision would be made based on a detection statistic rather than a probability, only the fusion process will be done in this method. In the DSmT, six fusion rules called PCR1-PCR6 have been proposed.[41] From the PCR1 up to the PCR6, one increases on the one hand, the complexity of the rules, but on the other hand, one improves the accuracy of the redistribution of conflicting information. In this method, since all experiments are conducted in a non-real-time way, the fusion method is designed by following the PCR6 to do the decision-level fusion.

The main idea behind the PCR6 is redistributing the conflicting information to hypotheses to make a more reasonable and comprehensive decision. When the conflict between channels is minor, it has similar fusion results to the classic Dempster-Shafer theory.[13] When the conflict becomes major, more reasonable decisions can be made by following the PCR6. More details about the PCR6 can be found in Ref. 41.

In the TWA detection, since the problem has only two potential hypotheses, present ($\mathcal{H}_1$) or not ($\mathcal{H}_0$), the single-channel characteristic parameters can be fused by

$$e_l^X = \prod_{k=1}^{K} e_{k,l}^X + \sum_{\Phi_1,\Phi_2} \frac{\prod_{k\in\Phi_1} e_{k,l}^X \prod_{k\in\Phi_2} e_{k,l}^Y \sum_{k\in\Phi_1} e_{k,l}^X}{\sum_{k\in\Phi_1} e_{k,l}^X + \sum_{k\in\Phi_2} e_{k,l}^Y}, \quad (7)$$

where sets $\Phi_1 \neq \emptyset$ and $\Phi_2 \neq \emptyset$ satisfy

$$\Phi_1 \cap \Phi_2 = \emptyset, \quad (8)$$

$$\Phi_1 \cup \Phi_2 = \{1, 2, \ldots, K\}, \quad (9)$$

and

$$X = \begin{cases} \mathrm{A}, & \text{for } Y = \mathrm{B}, \quad (10a) \\ \mathrm{B}, & \text{for } Y = \mathrm{A}. \quad (10b) \end{cases}$$

D. Decision making

After the fusion process, the decision making should be done to decide about the presence ($\mathcal{H}_1$) or absence ($\mathcal{H}_0$) of TWA in the multichannel ECG.

Similar to the single-channel decision making process,[14] the detection statistics are calculated as

$$S_l = \frac{e_l^{\mathrm{A}}}{e_l^{\mathrm{B}}}. \quad (11)$$

Considering the transient, non-stationary nature of TWA, the final detection statistic is obtained by

$$S = max\{S_l|_{l=1}^{L}\}. \quad (12)$$

Finally, the decision making can be done as

$$S \underset{\mathcal{H}_1}{\overset{\mathcal{H}_0}{\lessgtr}} \gamma, \quad (13)$$

where γ is the threshold that will be determined experimentally.

IV. EXPERIMENT SETTING AND DATA SET

Both simulated and real multichannel ECG records are used to evaluate the performance of the proposed method. How these ECG records are simulated, recorded, and picked out is shown as follows.

A. Simulated multichannel ECG records

Simulated ECG records and the corresponding simulation study are vital. That is because the actual presence of TWA in a real record is unknown in the clinical environment. Thus, since most parameters (ANR, TWA dimensionality, and the waveform) are known as prior information of simulated records, a Monte Carlo simulation approach is applied to evaluate the detection performance.

The synthesis process of the multichannel ECG record with a high degree of realism is shown in Fig. 3. For different simulation setups, the simulated records are with different ANRs and different types of the TWA waveform. With the same simulation setup, the simulated records are added with different realizations of real recorded noise. The clean ECG records from the healthy people in the Physikalish-Technische Bundesanstalt (PTB) diagnostic database[42–44] are used to synthesize the background ECG. The real recorded noise used in

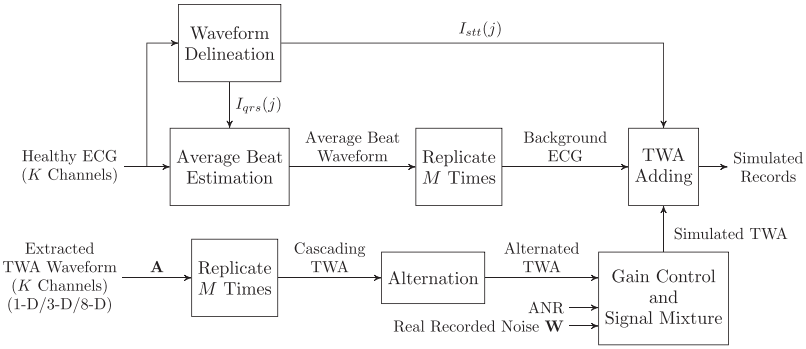

FIG. 3. General block diagram of the simulation setup.

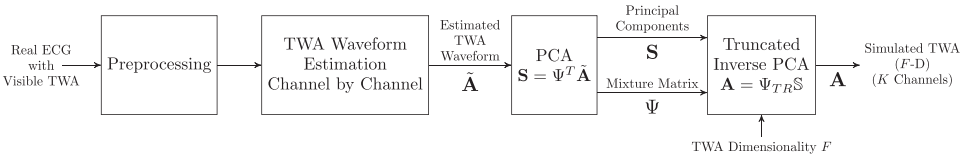

FIG. 4. General block diagram of the TWA waveform extraction.

synthesizing is the muscular activity noise from the MIT-BIH Noise Stress Test Database.[42] More details about the noise record can be found in Ref. 45. It is worth noting that the muscular activity noise record also contains electrode motion noise inevitably, which means that it is the most realistic noise record among others in the database. The real recorded noise is first resampled from 360 Hz to 1000 Hz. With the same simulation setup, segments of noise with the same length and random offsets are used to realize different simulated records. Since the background ECG is an interference that can be easily removed, the notion of the ANR is widely introduced to reflect the level of noise in the simulation study.[25,46,47] It is defined as the averaged relationship between the alternant wave power and the noise power,

$$\mathrm{ANR} = 10 \log \frac{M \sum_k^{k=K} \sum_p^{p=P} a_{p,k}^2}{\sum_k^{k=K} \sum_n^{n=N} w_{n,k}^2}, \tag{14}$$

where $a_{p,k}$ and $w_{n,k}$ are the elements of the TWA waveform $\mathbf{A}$ and the noise $\mathbf{W}$, respectively, in Fig. 3, and M is the number of beats that replicated in a simulation ECG record.

There are three kinds of TWA used in the simulation study. All these three kinds of TWA with different dimensionality (F = 1, 3, 8) are simulated as in Fig. 4. The 1-D TWA is the most common setup that is used in TWA simulation studies. The 3-D TWA is a result of the compromise between contents of TWA and noises. Because for most cardiac signals, the 3-D representation accounts for 80%–90% of the power of the body-surface potentials.[48,49] Besides, since only 8 leads are independent in the traditional 12-lead setup, the 8-D TWA is also used in the simulation study to describe the TWA as fully as possible.

The F-D TWA waveform is estimated as in Eq. (3) channel by channel, after the decomposition of PCA and the signal reconstruction by the truncated inverse PCA. Let the maximum likelihood estimation of the alternant waveform estimation by Eq. (3) be $\tilde{\mathbf{A}}$. The PCA decomposition of the estimated TWA waveform can be expressed as

$$\mathbf{S} = \Psi^T \tilde{\mathbf{A}}, \tag{15}$$

and then the F-D TWA is reconstructed by

$$\mathbf{A} = \Psi_{TR}\mathbf{S}, \tag{16}$$

where $\Psi_{TR} = \Psi\Lambda$ and Λ is a diagonal matrix that satisfies

$$diag(\Lambda) = \Big[\overbrace{1, 1, \ldots, 1}^{F}, 0, \ldots, 0\Big]. \tag{17}$$

With this TWA synthesis scheme, not only the dimensionality of the TWA waveform is considered but also the relative relationship between TWA in different channels is reserved.

It is worth noting that the multi-dimensional TWA is used to mimic the multi-source nature of TWA and the nonlinear propagation. The multiple sources of TWA are mainly determined by specific causes and their positions, which vary from person to person. The nonlinear propagation also varies for many factors such as the health condition, the position error of the electrodes, and even the posture during recording. So it is hard to describe them quantitatively. However, with the assumption of linear mixture, these characteristics can be regarded as multi-dimensional dispersions. So the multi-dimensional TWA extracted from real records are used in the experiments.

B. Real ECG records with diagnoses

Since some features in the real ECG are hard to be fully described by the linear mixture model used in the simulation study, the experiments on real ECG records are also very important. It is worth noting that the TWA has a transient feature, which indicates that TWA does not always exist in real ECG records. But as a risk stratification marker of the arrhythmia that has been prospectively demonstrated in more than 7200 patients,[50] the performance of detection methods could be assessed statistically in some degree by distinguishing arrhythmia patients from health subjects. Besides, the situation in the clinical environment is much more complex than simulation. When facing real ECG records, especially for those from patients, more bias between physical truth and simulation setups may exist, which will lead to completely different detection results. Therefore, the detection results on real records are also important references for the validity evaluation.

As an example of application to real records, the TWA detection was performed on one set of real records from the Physikalisch-Technische Bundesanstalt (PTB) diagnostic

TABLE I. Implementation details for the methods.

Method	Linear transformation	One-dimensional analysis	Multichannel decision
Single-v3	None	Laplacian likelihood ratio (LLR)	None (fixed lead v3)
Multi-OR	None	Laplacian likelihood ratio (LLR)	Hard-decision (OR)
Multi-πCA	πCA	Laplacian likelihood ratio (LLR)	Hard-decision (OR)
Multi-DSmT	None	Characteristic parameter extraction	Decision-level fusion

database.[42–44] This database was provided by the National Metrology Institute of Germany. These records were collected by Oeff from patients and healthy volunteers with detailed clinical summaries. Each record was digitized at 1000 samples per second (Hz), with a 16 bit resolution over a range of ±16.384 mV with 15 channels, which include 12 channels from the conventional leads and 3 channels from the Frank XYZ leads.

All the real records that are used in these experiments were picked out from this database as follows. To avoid the influence from different causes, only records from the myocardial infarction patients (368 records) and the healthy controls (80 records) are used. But not all these records are suitable for TWA detection. Some of them (20 records) have too few beats, some of them (9 records) have strong interference, such as artificial impulses from implantable cardioverter defibrillators, huge beat-to-beat variability, consecutive anomalous beats, and electrode detaching, and some others (27 records) are just too noisy to accomplish the delineation. If these records appear in clinical trails, re-recording is the most common approach to deal with this situation. In this experiment, all these records will be discarded and the remaining 392 records are classified into two groups.

1. *Myocardial infarction group*: This is the experimental group that is composed of 316 records with "myocardial infarction" in affiliated diagnosis.
2. *Healthy control group*: This is the control group that is composed of 72 records with "healthy control" in affiliated diagnosis. All these records are collected from healthy volunteers who have never had a heart-related disorder or disease.

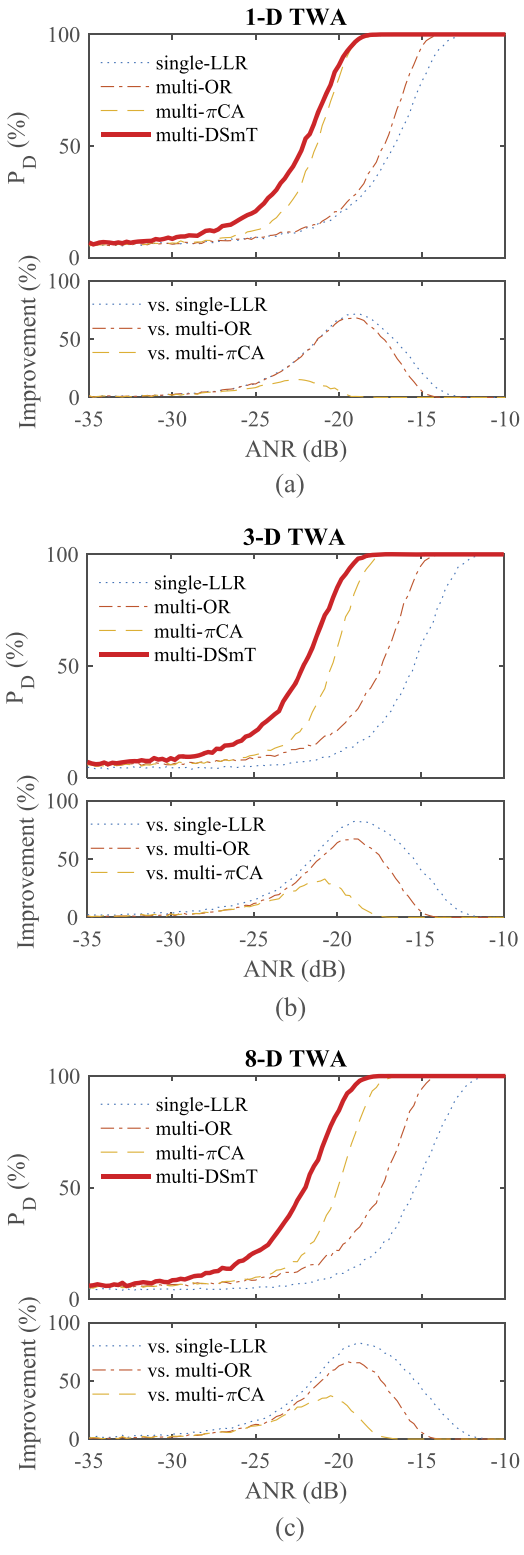

FIG. 5. Detection results P_D (top) and corresponding improvement between the multi-DSmT and other three methods (bottom) of experiments on simulated records with (a) 1-D, (b) 3-D, and (c) 8-D TWA.

V. EXPERIMENT RESULTS

Totally four schemes were performed and compared in these experiments. They are the standard single channel LLR scheme with lead v3 (single-v3), the LLR with "OR" strategy (multi-OR), the multichannel scheme based on πCA proposed in Ref. 34 (multi-πCA), and the proposed multichannel method in this paper (multi-DSmT). The main differences among these methods are shown in Table I. The results of these experiments are shown as follows.

A. Simulation study

In the simulation study, the detection performances of different methods were evaluated and compared by detection rates with different ANRs. In a detection problem, the detection performance is usually jointly evaluated by the true

TABLE II. TWA detection results of the experiments on the simulated ECGs with different types of TWA (1-D/3-D/8-D).

		TWA		
Parameter	Method	1-D	3-D	8-D
Equivalent minimum ANR $\mathcal{R}$ (dB)	Single-v3	−17.49	−15.81	−15.78
	Multi-OR	−18.19	−18.16	−18.28
	Multi-πCA	−21.88	−20.85	−20.61
	Multi-DSmT	−22.89	−22.73	−22.79
Maximum P_D improvement of multi-DSmT (%)	vs. single-v3	71.64	82.28	82.64
	vs. multi-OR	68.44	67.28	66.52
	vs. multi-πCA	15.38	32.94	37.18

positive rate (TPR, i.e., detection rate P_D) and the false positive rate (FPR, i.e., false alarm rate P_{FA}). In this simulation study, the TPR/FPR, also called sensitivity/specificity, is defined as the proportion of records with positive detection results while all the tested records are with/without TWA. To compare the performance in a more intuitive way, the threshold that makes the FPR $P_{FA} = 0.05$ is first calculated, and then the detection rate is calculated with this threshold. For each simulation setup (specific ANR and specific type of TWA), 5000 records were simulated. The duration of each record is 33 beats ($M = 33$).

The resulting detection rates with different ANRs are shown in Fig. 5 (top) and the differences between the multi-DSmT and the other three methods are shown in Fig. 5 (bottom). The equivalent minimum ANR and the maximum P_D improvement of the multi-DSmT are also calculated and shown in Table II. The equivalent minimum ANR is defined as

$$\mathcal{R} = r - \frac{\int_{-\infty}^{a} (P_D(\xi) - P_{FA})\, d\xi}{1 - P_{FA}}, \tag{18}$$

where $P_D(\xi)$ is the detection rate when the ANR is ξ and r is the ANR that is big enough to make $P_D(r) = 1$. According to this definition, a lower $\mathcal{R}$ would indicate a better detection performance.

To compare detection results of the records simulated with specific simulation setup, the receiver operating characteristic (ROC) curves (ANR = −20 dB) are calculated and shown in Fig. 6. The ROC curve is drawn by linking points $[P_{FA}(\gamma), P_D(\gamma)]$ where the threshold γ varies from 0 to $+\infty$. The ROC curve can be further evaluated by the maximum Youden's J statistic (J_{max}) and the area under curves (AUC), which are also calculated and shown in Table III. In the TWA detection problem, J_{max} means the maximum possible difference between P_D and P_{FA} with certain threshold γ. Besides, the high AUC indicates the low sensitivity to the threshold γ, which will be a great help to the determination of the threshold γ in clinical trails.

As the TWA information from different dimensions becomes more competitive (TWA from 1-D to 8-D), the differences of detection performance of the methods become more evident. When the records are simulated with the 1-D TWA, most information is consistent and can be expressed into one dimension by the linear transformation. So the detection performance of the multi-DSmT and the multi-πCA is almost the same [see Figs. 5(a) and 6(a)]. When the 8-D TWA is used, the information from different channels become more competitive with each other. By utilizing the highly competitive part of the information rather than discarding it, the proposed multi-DSmT shows more accurate and more robust performance.

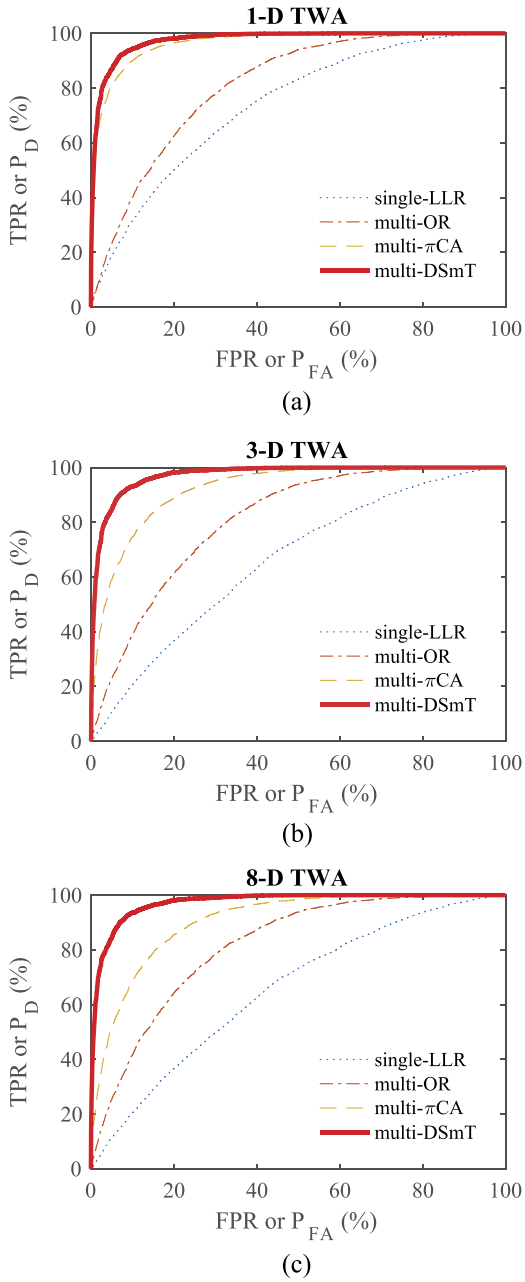

FIG. 6. ROC curves of detection results on simulated records (ANR = −20 dB) with (a) 1-D, (b) 3-D, and (c) 8-D TWA.

The slope of each detection curve in Fig. 5 reflects the robustness to noise. It can be observed that the multi-πCA is

TABLE III. Feature parameters of ROC curves of simulation detection results with ANR = −20 DB.

	Maximum Youden's J statistics (%)			Area under curves AUC (%)		
Methods	1-D TWA	3-D TWA	8-D TWA	1-D TWA	3-D TWA	8-D TWA
Single-LLR	35.46	24.76	23.98	73.85	65.85	65.45
Multi-OR	48.74	47.88	49.00	81.18	80.80	81.54
Multi-πCA	80.36	69.22	65.56	96.52	92.31	90.60
Multi-DSmT	84.94	83.58	83.86	97.65	97.35	97.38

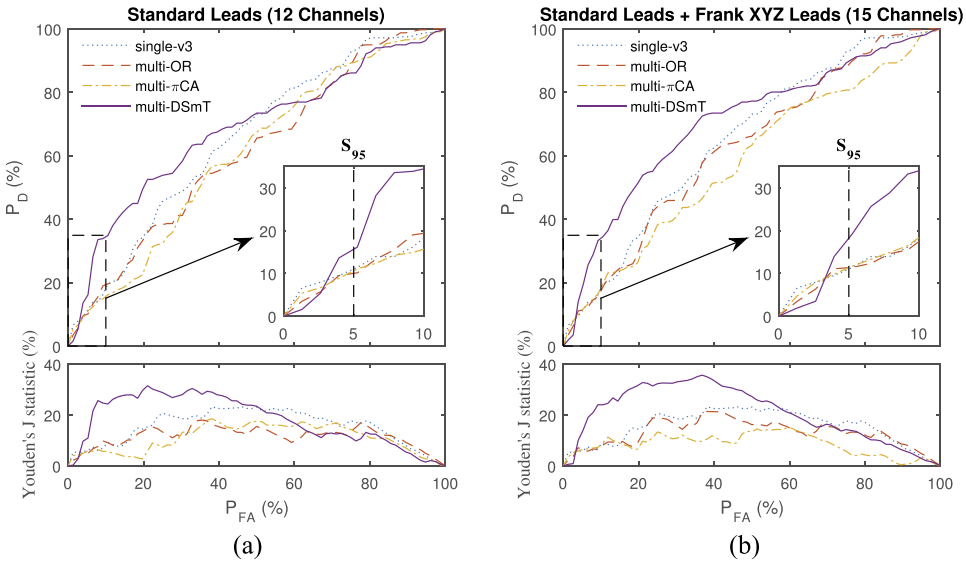

FIG. 7. ROC curves (top) and corresponding Youden's J statistic (bottom) of detection results on real records from the PTB database. (a) 12 channels and (b) 15 channels are, respectively, used in these experiments.

TABLE IV. TWA detection results of real ECG records from the PTB database.

		Detection results[a]		ROC curves (%)		
Involved ECG lead(s)	Methods	Healthy control	Myocardial infarction	J_{max}	AUC	S_{95}
Lead v3	Single-LLR	$(3.02 \pm 2.10) \times 10^{-2}$	$(4.86 \pm 6.60) \times 10^{-2}$	23.25	65.16	11.01
Standard leads	Multi-OR	$(7.49 \pm 4.05) \times 10^{-2}$	$(9.70 \pm 8.29) \times 10^{-2}$	17.95	61.35	10.00
(12 channels)	Multi-πCA	$(1.23 \pm 0.49) \times 10^{-1}$	$(1.55 \pm 1.34) \times 10^{-1}$	18.49	60.73	10.63
	Multi-DSmT	$(1.55 \pm 1.11) \times 10^{-4}$	$(2.59 \pm 7.61) \times 10^{-4}$	31.48	67.98	15.63
Standard leads +	Multi-OR	$(7.94 \pm 4.09) \times 10^{-2}$	$(1.06 \pm 1.10) \times 10^{-1}$	21.34	62.75	11.33
Frank XYZ leads	Multi-πCA	$(1.44 \pm 0.59) \times 10^{-1}$	$(1.76 \pm 1.38) \times 10^{-1}$	14.84	58.36	11.33
(15 channels)	Multi-DSmT	$(1.59 \pm 1.10) \times 10^{-4}$	$(2.55 \pm 6.43) \times 10^{-4}$	35.63	70.40	18.23

[a]Expressed as mean ± one standard deviation.

more sensitive to noise than the multi-DSmT. That is because the linear transformation is determined by statistical parameters, whose errors will increase when noises become stronger. The output TWA components may be harmed by the biased linear transformation. These errors will be delivered to the following analysis and decision process, resulting in relatively low robustness to noises.

B. Experiments on real records

For real records, their ANRs and the TWA in each channel are different and unknown, so the detection results are only evaluated by the ROC curve, which has been shown in Fig. 7 (top). The corresponding Youden's J statistics are shown in Fig. 7 (bottom). The same four detection methods as evaluated in the simulation study were performed on the two groups of the real ECG records. Furthermore, the detection results, the J_{max}, and the AUC of ROC curves are also calculated and shown in Table IV. In clinical trails, the low FPR P_{FA} usually has a higher priority than the TPR P_D, so a parameter called S_{95} proposed in Ref. 25 is also calculated and shown in Table IV. It is worth noting that the accuracy and the reliability of S_{95} obtained in these experiments are relatively low. That is because the number of records in the healthy control group is too small and the threshold γ is mainly determined by no more than 4 records (5% of 72), which is more likely to be influenced by outliers.

As the extra channels are used (from 12 channels to 15 channels) in the experiments, it can be observed that the multi-DSmT gets better performance while the multi-πCA gets worse. That is because the extra channels make the information more competitive. So more information will be discarded by multi-πCA, resulting in a lower information utilization and a lower detection accuracy. On the contrary, the multi-DSmT gets better detection performance by utilizing the extra information.

VI. DISCUSSION

According to the experimental results, detection accuracy is closely related to how highly competitive information is dealt with. Due to the effect of the noises and the multi-dimensional nature of TWA, uncertain and competitive information is inevitable. To reach a consensus on the final decision, most existing methods discard partial information to reduce conflict, resulting in the loss of important information. By utilizing this competitive information in a more reasonable

and comprehensive way, the proposed method can achieve more accurate detection results and more robust detection performance.

The proposed decision-level fusion method cannot be directly applied after the linear transformations such as πCA. That is because the linear transformation is aimed at improving the ANR of a certain dimension at the cost of ANR deterioration in other dimensions, which will make the information between dimensions more competitive. When one-dimensional decision method such as hard-decision "OR" method is applied, it will improve the performance greatly by just choosing a certain dimension with higher ANR. But when the proposed decision-level fusion method is applied to make the final decision, the ANRs in all channels are required to be as high as possible. So the direct combination of the linear transformation and the proposed method will result in a very low detection accuracy.

It is worth noting that the performance of multi-πCA is much worse than it is in the simulation study. There are two possible explanations for this strange result. First, the real records used in the experiments are limited. They cannot represent all situations in clinical trails. More real ECG records may be needed to get the more accurate assessment of the detection performance. Second, it may be caused by the errors from the linear transformation, which requires linear mixture of all sources and each component should be stationary. However, the TWA in the body-surface ECG is a non-stationary signal and has been distorted by a nonlinear propagation through the thorax. These differences may become more evident in the experiments with real records and deteriorate the detection performance.

Some disadvantages of the proposed method should also be noted. Since the single-channel analysis results are nonlinearly fused, the most obvious disadvantage is that no TWA estimation has been done in the proposed method. If the global TWA amplitude or waveform is required, the additional method for TWA estimation is needed.

Another disadvantage is the increased computation. Compared with the hard-decision "OR" method, the redistribution process for competitive information will bring extra computation. However, since the speed of ECG beats is relatively slow, real-time TWA detection by the multi-DSmT can be easily achieved by a general-purpose computer based on the analysis window scheme used in this study ($W = 32$, $D = 1$). In practical applications, if the computing power is very limited, the calculation can be reduced by using a larger shift parameter D of the sliding analysis window at the cost of a lower temporal resolution.

To further improve the situation, the implementation code has been optimized for the TWA detection. Since the number of hypotheses and input channels are fixed and known before fusion in the TWA detection, the addressing indices are identical in each fusion. Based on this fact, all indices can be calculated and stored once and for all before fusion. So the computation amount would be reduced at the cost of more random access memory (RAM) usage. Compared with the general implementation method proposed in Ref. 51, this customized method reduces the computation dramatically.

The proposed method is far from perfect and further work is needed. According to the clinical experience and the experiments on real records, we found that the TWA distribution among channels is not completely random. For the single-channel method, some channels (from v1 to v3) have a higher detection accuracy than the other channels. It suggests that the detection results from different channels have different confidence, and equal treatment to them in the fusion process is not fitting. Thus a weighted decision-level fusion method such as the DSmT with analytic hierarchy process (DSmT-APH)[52] may be able to further improve the detection performance. How to measure the weight coefficients for different channels will be the focus in the following researches.

VII. CONCLUSION

A novel multichannel decision-level fusion method for TWA detection was proposed. It was compared to single-channel and multichannel methods in both the simulation study and the experiments with real ECG records. The simulation study showed that the proposed method could utilize the competitive information from different channels and dimensions in a more reasonable and comprehensive way. By taking all channels into consideration in the decision process, the information utilization is improved. With the higher information utilization rate, the proposed method showed a higher detection accuracy and stronger robustness to noises. The results of the experiments with real ECG records showed that the proposed method also showed higher accuracy in distinguishing patients with myocardial infarction from healthy people through the TWA detection. Since the proposed method is designed to detect TWA channel-by-channel, it also reduces the demands on the sampling process of the ECG recorder.

ACKNOWLEDGMENTS

This work was supported in part by the National Natural Science Foundation of China (Grant Nos. 61671452 and 61471073) and Natural Science Foundation of Chongqing (Grant Nos. Cstc2014pt-sy40003, Cstc2015jcyjBX0078, and Cstc2016jcyjA0556).

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