V. Conclusion

In this paper, we proposed a heart rate indication system using sound with pitch and interval decided corresponding to instantaneous heart rates in real-time. We discussed the evaluation results of the biofeedback effects during work as an application example of this system.

This system uses an ECG which can be measured easily. Because it can be converted to sound in real-time and presented via a sound source, it is expected to be applied for biofeedback to monitor and improve biological conditions.

We compared the case where sound was presented using the proposed system with the case where work was performed without sound. Subjective effects differed among subjects. But even when a subject felt subjective workload, the physiological workload measured from the heart rate variability turned out to be rather smaller than when no sound was presented. On the other hand, the subjects who did not feel subjective workload because of the sound improved work performance. This result indicates the possibility of the biofeedback effect of this system.

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Study of Features Based on Nonlinear Dynamical Modeling in ECG Arrhythmia Detection and Classification

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***Abstract*—We present a study of the nonlinear dynamics of electrocardiogram (ECG) signals for arrhythmia characterization. The correlation dimension and largest Lyapunov exponent are used to model the chaotic nature of five different classes of ECG signals. The model parameters are evaluated for a large number of real ECG signals within each class and the results are reported. The presented algorithms allow automatic calculation of the features. The statistical analysis of the calculated features indicates that they differ significantly between normal heart rhythm and the different arrhythmia types and, hence, can be rather useful in ECG arrhythmia detection. On the other hand, the results indicate that the discrimination between different arrhythmia types is difficult using such features. The results of this work are supported by statistical analysis that provides a clear outline for the potential uses and limitations of these features.**

***Index Terms*—Arrhythmia detection, chaos theory, ECG, statistical classifiers.**

I. Introduction

Conventional methods of monitoring and diagnosing arrhythmia rely on detecting the presence of particular signal features by a human observer. Due to the large number of patients in intensive care units and the need for continuous observation of such conditions, several techniques for automated arrhythmia detection have been developed in the past ten years to attempt to solve this problem. Such techniques work by transforming the mostly qualitative diagnostic criteria into a more objective quantitative signal feature classification problem. Classical techniques have been used to address this problem such as the analysis of electrocardiogram (ECG) signals for arrhythmia detection using the autocorrelation function [1], using frequency domain features [2], using time frequency analysis [3], and wavelet transform [4], [5]. Other techniques used adaptive filtering [6], sequential hypothesis testing [7], [8], as well as morphological features. Even though fairly good results have been obtained using such techniques, they seem to provide only a limited amount of information about the signal because they ignore the underlying nonlinear signal dynamics.

In the last two decades, there has been an increasing interest in applying techniques from the domains of nonlinear analysis and chaos theory in studying biological systems [9]. In [10] and [11], the ECG signal was subjected to a variety of tests designed to detect nonlinear dynamics and showed evidence that the dynamics underlying the cardiac signals is nonlinear and indicate the possibility of deterministic chaos. Even though the results from such research did not form a definite proof of that, they showed that the dynamics was consistent with such a process.

In the field of chaotic dynamical system theory, several features can be used to describe system dynamics including correlation dimension (D_2), Lyapunov exponents (λ_k), approximate entropy, etc. These features have been used to explain ECG signal behavior by several studies (cf., [12]). Nevertheless, these studies applied such techniques only

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to a few sample ECG signals that did not allow the extraction of a general statistical description of the dynamics of different arrhythmia types. Moreover, the details of implementation of feature extraction techniques were not discussed. Given that such techniques are particularly sensitive to parameter variations, it is not possible to directly utilize these results or attempt to draw conclusions based on these studies about the robustness of their implementations. Therefore, a study that involves the analysis of ECG chaotic behavior based on a large number of signals using a more-detailed implementation of the feature extraction steps would be rather useful to show the advantages and the limitations of such class of nonlinear analysis.

In this paper , we address the problem of characterizing the nonlinear dynamics of the ECG signal and its variation with different arrhythmia types. The implementation details to automatically compute two important chaotic system parameters namely, the correlation dimension and largest Lyapunov exponent, are discussed. The proposed implementations were used to compute these features for a large number of independent ECG signals belonging to five different ECG signal types from the MIT-BIH Arrhythmia Database [13]. The results are studied to detect statistically significant differences among different arrhythmia types. Finally, statistical classification techniques are used to assess the possibility of detecting and classifying arrhythmia using such parameters.

II. Correlation Dimension Estimation

The mathematical description of a dynamical system consists of two parts: the *state* which is a snapshot of the process at a given instant in time and the *dynamics* which is the set of rules by which the states evolve over time. In the case of the heart as a dynamical system, the available information about the system is a set of ECG measurements from skin-mounted sensors. There is no mathematical description of the underlying dynamics of the heart. That is, we deal only with observables whose mathematical formulation and total number of state variables is not known. Therefore, to study the dynamics of such system, we first need to reconstruct the state space trajectory. The most common method to do this is using delay time embedding theorem to create a larger dimensional geometric object by embedding into a larger m-dimensional embedding space [14]. The embedding dimension m must be large enough for delay time embedding to work. When a suitable m value is used, the orbits of the system do not cross each other. This condition is tested using the false nearest neighbor (FNN) algorithm [9]. The dimension m in which false neighbors disappear is the smallest dimension that can be used for the given data.

The simplest way to think about the dimension D of an object is that it represents the exponent that scales the bulk b of an object with linear distance r (i.e., $b \, \alpha \, r^D$). The Grassberger–Procaccia algorithm uses a correlation integral $C(r)$ to represent the bulk, which is defined as the average number of neighbors each point has within a given distance r [14]. The correlation dimension D_2 is defined as the slope of the linear region of the plot of $\log(C(r))$ versus $\log(r)$ for small values of r. In practice, the determination of the linear scaling region is not an easy task because of the presence of noise, which makes it not practical to compute the slope for very small values of r. Moreover, this determination was found to be not repeatable using manual selection. In our implementation, we tried this approach combined with computerized regression and the results were not satisfactory. Then, we improved our implementation using a second-order regression for the whole curve. The linear regression was then obtained for the part of this curve that appeared linear by vision. More consistent values for D_2 were obtained. Finally, we developed an automatic algorithm to determine the linear region to eliminate the need for human interaction. This algorithm computes the second derivative of the $\log(C(r))$ versus $\log(r)$ curve and searches for the longest plateau with values below a certain threshold (used here as 0.1). If more than one linear region are found to have the same length, the one that yields the maximum D_2 value (i.e., smaller values of r as per D_2 definition) is chosen.

TABLE I
COMPUTED VALUES FOR DYNAMICAL SYSTEM FEATURES (MEAN ± STANDARD DEVIATION)

Type	*Parameter*	
	D_2	λ_1
NR	3.27 ± 0.42	8.18 ± 3.63
VC	2.54 ± 0.39	17.36 ± 3.68
VT	3.07 ± 0.52	13.55 ± 7.24
VB	2.71 ± 0.40	12.11 ± 5.08
VF	2.93 ± 0.71	13.20 ± 4.45

TABLE II
P-VALUES OF POOLED T-TEST FOR D_2

Type	*VC*	*VT*	*VB*	*VF*
NR	<1.0e-16	0.0071	1.7e-14	0.0006
VC		1.96e-9	0.0148	0.0002
VT			3.01e-5	**0.2201**
VB				0.0309

TABLE III
P-VALUES OF POOLED T-TEST FOR λ_1

Type	*VC*	*VT*	*VB*	*VF*
NR	<1.0e-16	4.7e-7	1.16e-6	1.38e-10
VC		2.7e-4	6.0e-10	5.82e-8
VT			**0.1929**	**0.7396**
VB				**0.1976**

To estimate a suitable value for the embedding time lag L, previous work suggested selecting the value at which the autocorrelation function reaches 0, $1/e$, 0.5, or 0.1 [14], or as the value at which the first minimum of the mutual information function occurs [9]. Here, we followed another approach where the time window length is used to calculate L [15]. In particular, the time window length (W) is defined by the time spanned by each embedding vector as $W = (m-1)L$. After determining m using FFN, we select the optimal time window length (W) as the window length that maximizes the plateau length in the above D_2 estimation scheme [15]. In this paper, the first zero of the FNN criterion suggested a value of $m = 8$ and the optimal window length was found to be around 583 ms (i.e., 210 samples at 360 samples/s). Consequently, the time lag (L) was estimated to be 83 ms.

III. Lyapunov Exponents

Lyapunov exponents quantify the sensitivity of the system to initial conditions, which is an important feature of chaotic systems and describes how small changes in the state of a system grow at an exponential rate and eventually dominate the behavior. Lyapunov exponents are defined as the long time average exponential rates of divergence of nearby states. If a system has at least one positive Lyapunov exponent, then the system is chaotic. The larger the positive exponent, the more chaotic the system becomes (i.e., the shorter the time scale of system predictability). Lyapunov exponents will be arranged such that $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n$, where λ_1 and λ_n correspond to the most rapidly expanding and contracting principal axes, respectively. Therefore, λ_1 may be regarded as an estimator of the dominant chaotic behavior of a system.

In this paper, the largest Lyapunov exponent, λ_1, is calculated as a measure of the chaotic behavior of the system using the Wolf algorithm.[1] We used the provided software implementation of Wolf's

[1] Http://www.users.iterport.net/~wolf

TABLE IV
RESULTS FOR CLASSIFICATION PROBLEM USING DIFFERENT CLASSIFIERS (INCONCLUSIVE DECISION RATES IN PARENTHESES)

Classifier	*Specificity*	*Sensitivity for VC*	*Sensitivity for VT*	*Sensitivity for VB*	*Sensitivity for VF*
Min. Distance	81.25%	9.38%	6.25%	15.63%	6.25%
Bayes	65.63%	25.00%	0%	31.25%	28.13%
k-NN (k=1)	34.38%	18.75%	25.00%	40.63%	34.38%
k-NN (k=2)	33.33% (63%)	27.27% (66%)	0% (78%)	41.67% (63%)	18.18% (66%)
k-NN (k=3)	42.86% (34%)	20.00% (38%)	0% (31%)	42.11% (41%)	25.00% (25%)
k-NN (k=4)	52.00% (22%)	20.00% (22%)	0% (22%)	34.62% (19%)	20.00% (22%)
k-NN (k=5)	53.85% (19%)	19.23% (19%)	0% (13%)	40.00% (22%)	21.74% (28%)
k-NN (k=6)	59.26% (16%)	26.32% (41%)	0% (28%)	27.27% (31%)	13.64% (31%)
k-NN (k=12)	62.96% (16%)	18.52% (16%)	6.67% (6%)	32.14% (13%)	14.82% (16%)

algorithm. This software is divided into two programs: database generator (BASGEN) and fixed evolution time (FET). BASGEN is a preprocessing step that generates a database that is used by FET to determine the closest points to any specific point. FET does the main job of calculating the average exponential rate of divergence of short segments of the reconstructed orbit. There are a lot of parameters that need to be defined for the two programs. The parameters for BASGEN were taken as: embedding dimension $m = 4$, time delay $L = 60$, and grid resolution ires $= 20$. It should be noted that for Lyapunov exponent calculations, the embedding dimension m was chosen as D_2 rounded to the next highest integer [10]. Also, the grid resolution refers to the fact that BASGEN places the reconstructed data into a grid of dimension m, with a resolution of ires cells/side. This grid will be used later by FET to efficiently find nearest neighbors (NNs) to any point. The parameters for FET were set as follows. The time step was chosen as the sampling period. The evolution time (*evolve*) was chosen as 25. The minimum separation at replacement (*dismin*) was selected to be 0.01. When a replacement is decided, points whose distance from the kept point is less than *dismin* are rejected. The maximum separation at replacement (*dismax*) was chosen as 15% of the data range. Finally, the maximum orientation error (*thmax*) is selected to be 30.

TABLE V
RESULTS FOR DETECTION PROBLEM USING DIFFERENT CLASSIFIERS (INCONCLUSIVE DECISION RATES IN PARENTHESES)

Classifier	*Specificity*	*Sensitivity*
Min. Distance	81.25%	50.78%
Bayes	65.63%	67.97%
k-NN (k=1)	34.38%	75.00%
k-NN (k=2)	20.00% (38%)	86.67% (30%)
k-NN (k=3)	28.13%	78.91%
k-NN (k=4)	26.32% (41%)	83.96% (17%)
k-NN (k=5)	40.63%	80.45%
k-NN (k=6)	36.36% (31%)	85.05% (16%)
k-NN (k=12)	34.62% (19%)	85.84% (12%)

IV. RESULTS AND DISCUSSION

The proposed techniques were implemented and applied to ECG signals from the MIT-BIH Arrhythmia Database [13]. The data set used for this paper was composed of five different types including normal (NR), ventricular couplet (VC), ventricular tachycardia (VT), ventricular bigeminy (VB), and ventricular fibrillation (VF). Each type was represented by 64 independent signals for the design set and another 32 signals for the test with each signal 3 s long. The VF signals were sampled at 250 samples/s, while the others were sampled at 360 samples/s.

The results for computing D_2 and λ_1 for different ECG signal classes are shown in Table I. We observe noninteger correlation dimension D_2 values and positive sign of λ_1 for all types. The results generally support the hypothesis that cardiac electrical activity reflects a low-dimensional dynamic system behavior [10]. The p-values of the pooled t-test based on D_2 are shown in Table II. The p-values of the pooled t-test based on λ_1 are shown in Table III. The results confirm that normal ECG signals can be statistically differentiated from abnormal by both dynamical system features. On the other hand, these features are not successful in discriminating between different abnormal signals. In particular, when using D_2, there is a statistically significant difference between all pairs at the 5% level except between VB and VF, which are significant at the 10% level. Moreover, there was no statistically significant difference between VT and VF. This may somewhat be explained by the presence of similarities in dynamics between these types. Given the common nature of VT and VF of producing higher heart rate, this might explain the similarity between them in their underlying dynamics. This is particularly apparent in their λ_1 values. Similarly, for λ_1 it is not possible to find statistically significant difference between VT, VF, and VB. The lack of separation between VB and both VT and VF in their λ_1 values may be explained by the clinical observation that VB can lead to VT in some conditions [17]. Given that λ_1 values describe the sensitivity to the initial condition, this explains the observed similarity in this domain where VB eventually leads to the same chaotic behavior as VT and VF. These statistically insignificant differences represent fundamental limitations of these dynamical features in differentiating between abnormal arrhythmia types.

Using the calculated D_2 and λ_1 values as feature vector for each case in the test set, the results of classifying the five different ECG types are listed in Table IV using three different classifiers [16]. The results for detecting the presence of abnormality are shown in Table V. In Tables IV and V, the inconclusive decision rates usually encountered with k-NN classifiers appear within parentheses. Even though the ECG signal classes have been shown to be statistically different (with the exception of VT and VF), the observed poor classification results indicate that their distributions have significant overlap. This suggests the only possibility of using the proposed features in detecting the presence of abnormality rather than to specify the type of abnormality. The three classifiers implemented provide different receiver operating characteristics. Nevertheless, the results of these classifiers provide a general conclusion about the classification accuracy and the upper limits in the sensitivity and specificity values obtainable using the proposed features. For example, the minimum distance classifier appears to provide the best specificity in both the detection and classification problems. This comes at the price of lowest sensitivity. On the other extreme, the k-NN results generally indicate the highest detection rate among the three classifiers at the price of lowest specificity. The Bayes minimum error classifier seems to provide results in the middle. Among the different values of k of the k-NN classifier, the value of $k = 1$ in the classification problem and $k = 5$ in the detection problem seem to provide better results (observing the inconclusive decision rates).

The signal window length for this analysis was chosen such that it is less than 10 s. This is to satisfy the ANSI/AAMI EC13-1992 standard, which requires alarms for abnormal ECG signals to be activated within 10 s of their onset. The variation of the number of points within this duration was not found to be crucial as long as the ECG signal is sufficiently sampled.

V. Conclusion

The use of ECG signal features from nonlinear dynamical modeling was studied. The results from a large data set of actual ECG signals from five different classes were presented. The statistical analysis of the results suggests that the use of such features can be advantageous to ECG arrhythmia detection. They also illustrate the limitations of such features in classifying the type of ECG abnormality. Future work should address the use of such features among other classical statistical ECG features as well as more sophisticated classification techniques to improve the results.

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A Wavelet-Based Heart Rate Variability Analysis for the Study of Nonsustained Ventricular Tachycardia

Szi-Wen Chen

***Abstract*—It has been reported that the sympathovagal balance (SB) can be quantified by heart rate (HR) via the low-frequency (LF) to high-frequency (HF) spectral power ratio LF/HF. In this paper, an investigation of the relationship between the autonomic nervous system (ANS) and nonsustained ventricular tachycardia (NSVT) is presented. A wavelet transform (WT)-based approach for short-time heart rate variability (HRV) assessments is proposed for this aspect of analysis. The study was conducted on an RR-interval database consisting of 87 NSVT, 61 ischemic and five normal episodes. First, instantaneous SB estimates were generated by the proposed method. Then, waveforms of the WT-based SB evolutions were quantitatively examined. Numerical results showed that while a majority of SB waveforms (about 71%) derived from the non-NSVT population (i.e., ischemic and normal) appeared to come near oscillating with certain fixed levels, approximate 75% of SB evolutions underwent significantly rapid increases prior to the onset of NSVT, suggesting that an abrupt sympathovagal imbalance might partly account for the occurrence of NSVT.**

***Index Terms*—Autonomic nervous system, heart rate variability, nonsustained ventricular tachycardia, wavelets.**

I. Introduction

Nonsustained ventricular tachycardia (NSVT), defined as three or more consecutive ventricular premature beats (VPBs) with a rate of more than 120 beats/minute and lasting less than 30 s [1], is usually

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