ORIGINAL ARTICLES

Usefulness of Nonlinear Analysis of ECG Signals for Prediction of Inducibility of Sustained Ventricular Tachycardia by Programmed Ventricular Stimulation in Patients with Complex Spontaneous Ventricular Arrhythmias

Ornella Durin, M.D.,* Claudio Pedrinazzi, M.D.,* Giorgio Donato, M.D.,* Rita Pizzi, Ph.D.,† and Giuseppe Inama, M.D.*

*From the *Department of Cardiology, Ospedale Maggiore, Crema, Italy, and †Department of Information Technologies, University of Milan, Milan, Italy*

Introduction: The aim of our study was to assess the effectiveness of the nonlinear analysis (NLA) of ECG in predicting the results of invasive electrophysiologic study (EPS) in patients with ventricular arrhythmias.

Methods: We evaluated 25 patients with history of cardiac arrest, syncope, sustained, or non-sustained ventricular tachycardia (VT). All patients underwent electrophysiologic study (EPS) and nonlinear analysis (NLA) of ECG. The study group was compared with a control group of 25 healthy subjects, in order to define the normal range of NLA. ECG was processed in order to obtain numerical values, which were analyzed by nonlinear mathematical functions. Patients were classified through the application of a clustering procedure to the whole set of functions, and the correlation between the results of nonlinear analysis of ECG and EPS was tested.

Results: NLA assigned all patients with negative EPS to the same class of healthy subjects, whereas the patients in whom VT was inducible had been correctly and clearly isolated into a separate cluster. In our study, the result of NLA with application of the clustering technique was significantly correlated to that of EPS ($P < 0.001$), and was able to predict the result of EPS, with a negative predictive value of 100% and a positive predictive value of 100%.

Conclusions: NLA can predict the results of EPS with good negative and positive predictive value. However, further studies are needed in order to verify the usefulness of this noninvasive tool for sudden death risk stratification in patients with ventricular arrhythmias.

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ventricular arrhythmias; ECG; nonlinear analysis; electrophysiologic study

A current research aim is to optimize the prognostic evaluation of arrhythmic risk through noninvasive, cheaper, and easily applicable techniques. The present study, which forms part of such efforts, explores the possible clinical application of a completely new conceptual and methodological approach, namely the study of ECG signals through nonlinear mathematical functions.[1,2–4]

Over the last 20 years or so, this methodology has also been developing in the field of medicine.[1] This has especially been the case in cardiology, in which the analysis of electrocardiographic signals has proved to be particularly suited to the application of these mathematical techniques.[2] From the conceptual standpoint, research in this area stems directly from the study of heart rate variability, an approach that utilizes systems of linear calculation in both the time and frequency domains in order to analyze ECG signals. This approach, however, has not proved able to solve the problem of the

Address for reprints: Prof. Giuseppe Inama, Department of Cardiology, Ospedale Maggiore, L. go U. Dossena 2–26013 Crema, CR, Italy. Fax: 0039 (0)373 280036; E-mail: g.inama@hcrema.it

noninvasive stratification of subjects at high risk of sudden death.

A major determinant of this lack of efficacy seems to lie in the methodology itself. Indeed, attempts have so far been made to use linear equations to describe the variability of the ECG signal; this appears instead to be sustained by the complex interaction of several different systems, which would be better described by nonlinear calculations. It is precisely this complex interaction that underlies the component of deterministic chaos typical of the variability of the ECG time series in healthy subjects–individuals who are capable of satisfactory responses and adaptations to multiple, and often rapid, modifications of the internal and external environments.

It should, however, be pointed out that the deterministic chaos that characterizes a healthy biological system differs profoundly from completely random variability, in that the extremely complex variability of the former is endowed with a self-similarity (fractal) that repeats in different timescales (days, hours, minutes).[1] Similarly, it differs from the simple periodic variability that characterizes the ECG time series preceding serious cardiac arrhythmic events, which show a regular signal, dynamically characterized by limit cycles or punctual attractors. Indeed, a pathological substrate appears to be strictly bound to an increase in the order and regularity of the ECG dynamic system (or, by contrast, to the appearance of sharp randomness), displaying less flexibility and adaptability to great and sudden environmental changes.[1,5–7] On the basis of these considerations, it should be possible to detect changes in the chaoticity of the ECG signals, and thereby to evaluate the risk of developing life-threatening arrhythmias.

The aim of our study was to assess the effectiveness of the nonlinear analysis (NLA) of ECG in predicting the results of invasive electrophysiologic study (EPS) in patients with ventricular arrhythmias.

MATERIALS AND METHODS

Study Population

We retrospectively evaluated 28 patients admitted to our Electrophysiology Laboratory from 2000 to 2003 for EPS owing to a clinical history of aborted sudden cardiac death, sustained VT requiring emergency room admission, syncope of unknown origin or nonsustained VT evidenced by resting ECG or Holter monitoring. Sustained VT was defined as ventricular tachycardia more than 30 seconds in duration, whereas nonsustained ventricular tachycardia was defined as a sequence of more than three premature ventricular complexes, lasting less than 30 seconds. In our study group, none of the patients were on antiarrhythmic drugs at the time of arrhythmic event. The study group was then compared with a control group of 25 volunteer healthy subjects, who did not undergo EPS, in order to define the normal range of nonlinear analysis parameters. These subjects were comparable to the study group according to age and gender distribution. Their clinical history did not show the presence of previously diagnosed structural heart disease. Physical examination, resting ECG, and echocardiogram were normal. 24-hour Holter monitoring did not show the presence of ventricular arrhythmias.

ECG and Holter Monitoring

In all patients, the QT interval was manually measured in leads II, V_5, and V_6 by an experienced physician, with the longest value being used. The QT interval was then corrected using the Bazett's formula. Moreover, all patients underwent 24-hour ambulatory ECG monitoring. The average HR and number of premature ventricular complexes (PVC) per hour were automatically calculated (Pathfinder Digital, Del Mar Reynolds Medical Ltd, Edinburgh and Hartford UK, Irvine CA, USA). The RR interval series (tachograms) were automatically obtained; when artifacts or arrhythmia were present, corrections were made using appropriate software (HRV Tools v.1.73, Del Mar Reynolds Medical Ltd). A consecutive series of 300 beats, overlapped with 150 beats, was considered for the analysis (~600 series/day).

A series was automatically discharged if it did not contain at least 95% of sinus beats correctly recognized. Mean RR (ms) and the standard deviation of normal-to-normal RR intervals (SDNN) (ms) were calculated.

Electrophysiological Study

Electrophysiological study was always performed off antiarrhythmic drugs. A 6-French tetrapolar recording and stimulating catheter was inserted through the right femoral vein and positioned in the right ventricular apex. Programmed Ventricular Stimulation (PVS) was performed through an automatic stimulator (Micropace EPS 320) with up to three extrastimuli at basic cycle lengths of 600, 500 and 400 ms, down to the ventricular refractory period, but never <180 ms. The same protocol was then repeated with the catheter placed in the right ventricular outflow tract. EPS was considered positive if sustained monomorphic VT was induced.

Nonlinear Analysis of ECG Signals

ECG signals were recorded in the basal state in all subjects by means of the Polygraph Lab System Duo EP Laboratory (Bard Electrophysiology Division, Murray Hill, NJ, USA), before EPS was started, and always off antiarrhythmic drugs. We chose 20″ ECG strips, in sinus rhythm; their signals were then processed by means of an appropriate software, specifically developed by the Department of Information Technologies of the University of Milan, in order to obtain numerical values. These data were finally analyzed by nonlinear mathematical functions, as explained in detail below.

Nonlinear techniques for the automated detection of arrhythmias have been proposed in the past.[5–7] The results show that nonlinear analysis can be used to evaluate the complex dynamics of the heart by transforming qualitative diagnostic criteria into a quantitative problem. However, as such techniques are very sensitive to variations in parameters, it is not possible to use these results directly in clinical practice. We therefore adopted a combination of several discriminating nonlinear variables in order to draw conclusions by means of a clustering procedure that enables them to be evaluated comparatively without the need for absolute evaluation of parameters.

We treated the ECG time series on the basis of Recurrence Quantification Analysis.[8,9] A one-dimensional time series is extended to a higher dimensional space-time series by means of the delay-time embedding technique. In short, in order to extend a one-dimensional signal to an M-dimensional one, each observation in the original signal X(t) is substituted by a vector

$$y\ (i) = \{x\ (i),\ x\ (i,\ d),\ x\ (i,\ 2\ d), \ldots, x\ (i - (m-1)\ d\}$$

where i is the time index, M the embedding dimension, and d the delay time. This yields a series of vectors

$$Y = \{y\ (1),\ y\ (2),\ y(3), ., y\ (N - (m-1)\ d)$$

Once the dynamic system is reconstructed in this way, it is possible to process different quantitative functions in order to evaluate the peculiar features of the dynamic system itself.

Recurrent values consecutive in time of the series of quantitative estimates (Mutual Information, Entropy, Recurrence, Determinism, Ratio) are graphically represented in a Recurrence Plot (RP) by lines parallel to the principal diagonal; these lines are an important sign of deterministic structure. Indeed, it can be shown that the longest diagonal line corresponds to the value of the maximum Lyapounov exponent of the series. The Lyapounov exponent quantifies the mean rate of divergence of trajectories along the directions of the phase space. Chaotic systems have a positive maximum Lyapounov exponent.

A Recurrence Plot can highlight the hidden structure of the system and its internal structural changes. The basic idea of the RP is to form a color-coded matrix in which each [*i*][*j*]th entry is calculated as the Euclidean distance between all the pairs of vectors Y_i and Y_j in the reconstructed series and is codified as a color.

For random signals, the distribution of colors over the entire RP is expected to be uniform. The more deterministic the signal, the more structured the RP. Hot colors (yellow, red, orange) are associated with short distances between vectors; cold colors (blue, black) represent long distances. Signals with repeated fixed distances between vectors are organized, while those without repeated distances are not. In this way, we obtain uniform color distribution for random signals, but the more deterministic and self-similar the signal is, the more structured the plot is.

RP yield several quantitative functions that are useful in evaluating the internal structure of the dynamic system underlying the EEG signals.

We considered the following functions:

Mutual Information

We can define mutual information (MI) as a quantity that measures the mutual dependence of two random variables. Mutual information reflects the probability of finding a given time-series value in one interval and the probability of finding the same value in another interval after the delay time d. In the case of independence between the two variables, MI is zero; otherwise it is greater than zero.

Entropy

Entropy is calculated on the RP in both the space and time domains. This quantity compares the distribution of distances between all the pairs of vectors in the reconstructed space with the distribution of distances between the trajectories evolving in time. The function compares the global distribution of colors inside the RP with the distribution of colors on each diagonal line. The more evident the differences between the global distribution and the distributions in the single diagonal lines are, the more structured the image is, and the lower entropy is. Entropy is small when the longest segment parallel to the diagonal is short. High entropy is typical of periodic behavior, while low entropy indicates chaotic behavior.

Recurrence

This measures the percentage of recurrent points: a point *(i,j)* is recurrent if the distance between the vectors *y(i)* and *y(j)* is less than a given threshold, and the degree of recurrence is calculated as the ratio between the number of recurrent states measured and that of all the possible states.

Determinism

This is shown by the percentage of recurrent plots forming line segments parallel to the main diagonal. The presence of these lines reveals the existence of a deterministic structure.

Ratio

This function is the ratio between the value of determinism and the value of recurrence; it is therefore, an index of self-organization, that is, of a spatiotemporal structure that emerges spontaneously from the evolution of the system as a function of its dynamics.

After calculating these functions, we classified the patients by applying a clustering technique to the whole set of functions. Clustering is particularly suited to identifying regularities within large amounts of heterogeneous data.[10–12] When applied to a set of discriminating variables, the clustering method yields a global response, that is, it does not provide information on each single variable, but rather on the interaction among all the parameters used.

Hierarchical clustering algorithms have aroused great interest among biologists and physicians on account of their effectiveness. Their purpose is to organize data into a hierarchical structure that collects similar observations into small cluster at a lower level, and more basically connected observations into larger clusters, and so on throughout the whole set of data. In other words, the first partition of the sequence is represented by a unique set $C_1 = \{d_i | 1 < i < N\}$ including all the observations; the second partition forms $n_2 > 2$ disjointed subsets complementary to C_1 and so on, up to the last partition.

Hierarchical methods use several techniques for the fusion of observations. We used the so-called Average Group linkage, in which each group is represented by the mean value of each variable, and the intergroup distance is defined as the distance between two mean vectors. If we consider two hypothetical clusters, r and s, these are grouped together in such a way that their mean distance is the shortest one:

$$D(r, s) = Mean\ \{d(i, j) : \ where\ i\ and\ j\ are\ in\ the\ cluster\ t,\ formed\ by\ the\ union\ of\ r\ and\ s\}$$

In summary, cluster analysis is used to determine if a data set contains distinct groups and to identify them. The most commonly used clustering methods lead to a series of hierarchical classifications, summarized by a tree-diagram called a dendrogram. Differences between methods arise from the way in which the distances between groups can be defined. The average linkage measure is defined as the average of the distances between all pairs of objects where members of a pair are in different groups. This technique is known as a robust classifier and allows to evaluate a patients' grouping where the effect of the different variables for each patient is evaluated in their global interaction.

Statistical Analysis

Continuous variables are expressed as mean value ± standard deviation and were compared by means of an unpaired *t*-test. Categorical variables were compared by means of the Fisher's exact test or chi-square test with Yates' correction for continuity, where appropriate. Correlation between the results of EPS and those of nonlinear analysis of ECG signals was analyzed by means of logistic regression analysis. Furthermore, the negative and positive predictive value of nonlinear analysis of ECG signals was calculated in comparison with the result of EPS.

RESULTS

We excluded from the study three patients of the original study group because the quality of the ECG trace was insufficient for the application of nonlinear analysis software. The final study group was therefore made up of 25 patients (19 males, 76% of study group; mean age 50 ± 16 years, range 23–76 years) and a group of 25 healthy subjects of comparable age and gender (mean age 48 ± 12 years; 18 males). The control group subjects underwent nonlinear analysis of ECG signals, and the clustering procedure spontaneously assigned them to a homogeneous class. This result of nonlinear analysis is defined as "negative."

The patients were divided into two groups according to the result of EPS. Group A comprised 12 patients (48%) with negative EPS, while group B was made up of 13 patients (52%) with positive EPS. No significant differences were seen between the two groups in terms of age, gender, structural heart disease, or ejection fraction. By contrast, the groups significantly differed in terms of clinical presentation; specifically, a higher prevalence of non sustained VT was recorded in group B, while sustained ventricular tachycardia was more frequent in group A. We did not observe significant differences in the prevalence of syncope or ventricular fibrillation (VF), in corrected QT interval, in the number of premature ventricular complexes (PVC) and average HR at Holter ECG and in SDNN. (Table 1).

Nonlinear Analysis of ECG Signals

When the Hierarchical Clustering Technique was applied to these numerical values in accordance with the Average Group Linkage Method, it showed that all patients with negative EPS had been assigned to the class of healthy subjects, whereas the patients in whom VT was inducible had been correctly and sharply isolated into a separate cluster. In our study, the result of nonlinear analysis of ECG signals with application of the clustering technique was therefore significantly correlated to that of EPS ($P < 0.001$), and was able to predict

Table 1. Clinical and Demographic Data of the Study Group

	Group A	Group B	P
Age	46 ± 4	55 ± 5	0.15
Males	8 (61%)	11 (92%)	0.08
EF (%)	55 ± 3	48 ± 4	0.12
Heart disease			
Ischemic dilated cardiomyopathy	1 (8%)	4 (33%)	0.11
Coronary artery disease	4 (31%)	4 (33%)	0.89
ARVD	2 (15%)	2 (17%)	0.93
Hypertensive heart disease	3 (23%)	0 (0%)	0.20
Hypertrophic cardiomyopathy	1 (8%)	1 (8%)	0.95
No heart disease	2 (15%)	1 (8%)	0.59
Clinical presentation			
NSVT	11 (85%)	5 (42%)	0.02
VT	0 (0%)	5 (42%)	0.01
VF	1 (8%)	1 (8%)	0.95
PVC/h	80 ± 39	76 ± 32	0.64
Mean HR (beats/min)	68 ± 7	67 ± 7	0.64
QTc interval (ms)	429 ± 24	427 ± 24	0.89
SDNN	76 ± 10	72 ± 9	0.39
Unexplained syncope	1 (8%)	1 (8%)	0.95

ARVD = arrhythmogenic right ventricular disease; NSVT = nonsustained ventricular tachycardia; VT = sustained ventricular tachycardia; VF = ventricular fibrillation; PVC/h = premature ventricular complexes per hour; HR = heart rate; QTc = corrected QT; SDNN = standard deviation of RR intervals.

Table 2. Concordance between the Results of Nonlinear Analysis of ECG Signals and Electrophysiologic Study

	Negative EPS	Positive EPS
Negative NLA	12 (100%)	0 (0%)
Positive NLA	0 (0%)	13 (100%)

NLA = nonlinear analysis; EPS = electrophysiologic study.

the result of EPS, with a negative predictive value of 100% and a positive predictive value of 100% (Table 2).

Another analysis, performed directly on the graphical appearance of the RPs, showed other interesting features of the ECG signals of the patients examined. As described above, random signals in the RPs give rise to a uniform distribution of colors, whereas the more deterministic (or less chaotic) the signal, the more structured the plot (Figs. 1 and 2).

DISCUSSION

The accurate prognostic stratification of patients with complex hyperkinetic ventricular arrhythmias is, for many good reasons, a crucial problem. Sudden death remains a phenomenon of disturbing proportions, displaying a mean incidence of 300,000–350,000 persons/year in the USA (0.1–0.2% of the general population). In Europe, the figures are very similar. In 90% of cases, sudden death has an arrhythmic cause, the prevalence being particularly high in certain subgroups of patients, such as those affected by primary or ischemic heart disease with low EF (<30–35%), in whom (especially in the ischemic subjects) the incidence may reach 20% at 1 year and 50% at 2 years, particularly in the presence of some independent risk factors such as heart failure, advanced age, atrial fibrillation, QRS ≥ 120 ms, and chronic renal insufficiency.[13]

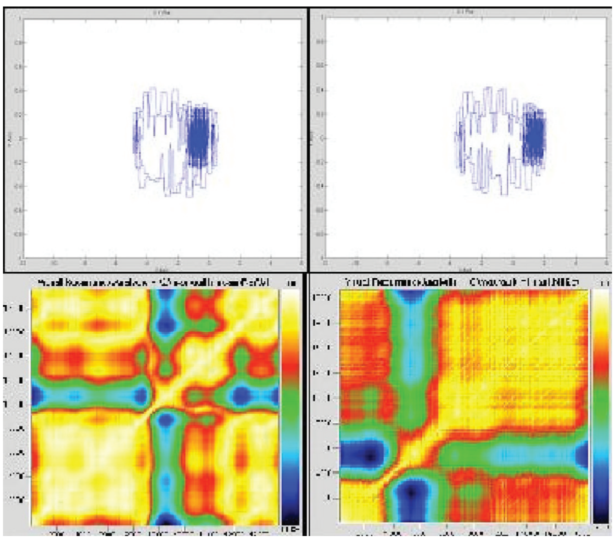

Figure 1. Recurrence Plots (bottom) and attractors (top) of healthy subjects. It is evident a massive presence of hot colors (red, yellow, orange) denotes small distances between vectors. The large bands of colors denote a chaotic behavior. Similarly, the chaotic behavior is shown by the wide area of figures in the attractors graphic representation.

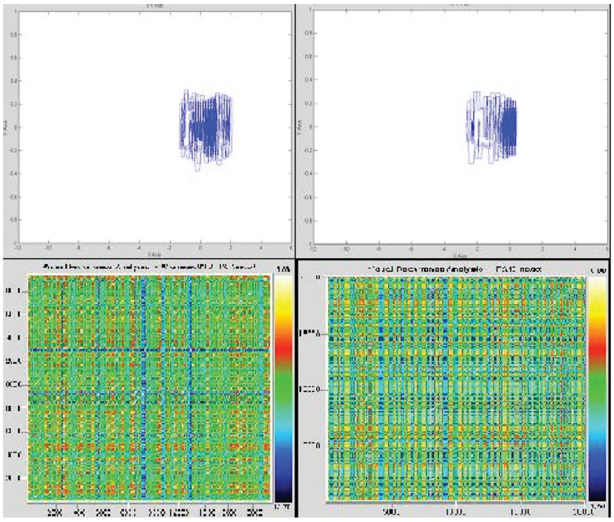

Figure 2. The plots of EPS-positive patients are heavily characterized by a quite regular distribution of colors, which is synonymous with deterministic (nonchaotic) signals, that is, signals that are more susceptible to forecasting than those of the first two groups. Similarly, graphic representation of attractors consists of figures with a very small area.

Studies such as the MUSTT and MADIT I and II[14,15] have clearly demonstrated the efficacy of implantable defibrillators in reducing long-term mortality in these subjects. At the same time, however, they have raised the considerable problem of cost, and therefore of clinical management, in that a decidedly high number of indications for implantation has emerged. Moreover, follow-up data in the literature seem to show clearly that the long-term benefits of this still costly treatment are enjoyed by only a portion of this population. In this context, one of the most pressing needs, in addition to that of reducing the cost of devices, is to improve the efficacy of risk stratification, which remains a weak spot in the struggle against arrhythmic death. Indeed, indexes such as EF are proving to be increasingly unsatisfactory, while the diagnostic tests available (EPS, Signal Averaging, HRV and Baroreflex, TWA),[3,4] though endowed with good negative predictive power (sometimes above 90%), display a positive predictive power that does not exceed 21–22% when used individually (30–40% in association). This criticism is applicable even to TWA, which was recently proposed by the 2006 ACC/AHA/ESC Guidelines as a type-IIA indication with level of evidence A.[16]

Efforts to improve the potential of tests for prognostic stratification are therefore far from misplaced, especially if stratification can be achieved through noninvasive means, which are less costly in both human and economic terms. Such efforts might usefully be directed to exploring completely new and exciting fields, such as that of the nonlinear dynamics of complex biological systems and of the mathematical functions utilized to describe them.

In our study, nonlinear mathematical functions were tested in patients in whom arrhythmic risk stratification was performed by means of EPS, patients who tested positive on EPS were classified according to predefined criteria as being at high risk. In EPS-positive patients, the functions produced clearly different results from those obtained in EPS-negative individuals and in normal control subjects; correspondence with the results of the invasive study was therefore excellent. A further interesting finding was that this correlation was totally independent of the underlying pathology and of other noninvasive parameters, such as corrected QT interval, heart rate, number of PVC per hour, and SDNN. This raises intriguing questions with regard to the possible biological variables involved in the modification of these parameters.

The method that we used differs from those presented in the literature in the last decade (see references in text and cited below) in that it is based neither on the linear or nonlinear filtering of ECG signals nor on the use of single nonlinear procedures; rather, it is based on the simultaneous evaluation of different nonlinear functions through a multivariate technique typical of data mining: hierarchical clustering. This approach reveals common characteristics of the time series of the ECGs of patients, which are searched for in the set of the various nonlinear functions calculated. In this way, we can avoid the risk of relying on a single technique; indeed, single techniques, however, advanced they may be, necessarily involve a degree of subjectivity in the choice of parameters, which may yield contradictory results. This is especially true of nonlinear techniques. As amply described in the text, our method is based on the analysis of Recurrent Plots, which yield, on the one hand, a series of quantitative estimates (Mutual Information, Entropy, Recurrence, Determinism, Ratio) and, on the other, an overall qualitative view of the ECG trace. As can be seen in Figures 1 and 2, this distinguishes between healthy patients and EPS-positive patients. Quantitative discrimination among patients is, by contrast, achieved through hierarchical clustering by applying the Average Group Linkage method, as described in the text. The clustering technique is applied to the above-mentioned quantitative variables and enables patients to be subdivided into discrete classes which coincide with those obtained through endocavitary electrophysiological study. The classification by means of clustering techniques takes into account the nonlinear interactions between variables. For this reason the presence of variables whose trend is apparently not significant can influence the final clustering result. Thus a first analysis should maintain the maximum information content before performing a variable reduction. However, a comparative evaluation of clustering results obtained after a PCA variable reduction, or the comparison with different NLA methods, are desirable and will be performed in the next future.

It is also interesting that the results of all the functions applied were concordant, even though those of some functions (recurrence, determinism, ratio, entropy) were particularly marked. It therefore seems reasonable to claim that it is the entire set that contributes to defining the dynamic features of the ECG signal in the subjects examined and which enables those with the greatest risk to be picked out from the rest of the group by means of the clustering procedure. These observations seem to point to a reduction in the dynamic organization of the electrocardiographic signal in those patients who are most compromised,[1,8,9,17] a finding that is in line with published data yielded by different nonlinear functions from those used in this study.

The available data show that the most commonly used functions are: The Power Law Slope,[2,10,17,18] the Short-Term Fractal Scaling Exponent (or Alpha

1 exponent), calculated by means of Detrended Fluctuation Analysis (DFA1),[11,12,17–23] the quantification of Poincaré Plots[21–23] and the Correlation Dimension (D2) (or modified calculation of the Pointwise Correlation Dimension),[10,23–25] the results of which have been subjected to the usual statistical evaluations; by contrast, the clustering procedure utilized in the present study appears to be totally different and innovative. In fact, it enables a series of consecutive points of the ECG signal to be transformed into a numerical series. The advantage of this mathematical approach is that it does not imply the analysis of a tachogram; therefore, no problems arise from the selection of the frequencies and the incorrect use of the filters.

Another undeniable advantage of the system of processing and calculation that we adopted is that it is based on "Short-Period Observation." This feature offers further advantages over systems based on "Long-Period Observation" (such as calculation of the Correlation Dimension or of the Power Law Slope). Our analysis enables relatively small amounts of information to be used, in that ECG strips of a duration of no more than 20 seconds are analyzed. This allows us: (1) To greatly simplify the collection of signals from an ECG recorder or a polygraph, without needing 12–24-hour Holter monitoring. (2) To ensure the quality of the signal, as there are no problems of noise caused by motion or defective contact of the electrodes. Moreover, we can choose the best ECG strip stored in the set memory, which can be used in retrospective analysis. (3) To minimize the problem of the variation and control of the initial state, to which the Chaotic Systems are, by definition, more sensitive. All these interesting peculiarities have favorable implications for the feasibility of application in everyday clinical practice, an aspect that should not be overlooked in view of the fact that the methods based on long-period analyses require a very broad range of data and therefore prolonged ECG recordings (24-hour Holter recordings for the Correlation Dimension and 12 hours for Power Law Slope calculation), features that are difficult to reconcile with the need to maintain acceptable stability of the system.

Our study applied a clustering procedure to the results obtained through the use of a set of nonlinear calculation functions. This enabled a group of patients at particularly high arrhythmic risk according to both clinical and electrophysiological criteria to be clearly picked out from lower-risk patients and normal control subjects; moreover, good agreement was seen between the results of the noninvasive evaluation and those of the invasive test. They are very encouraging results; however, because it was retrospective and based on a somewhat small sample, the study cannot claim to be more than a preliminary experience.

Unfortunately, the gold standard in the prognostic stratification of patients at risk of life-threatening events remains follow-up alone, as no test, or combination of tests, can as yet provide a reliable point of reference. Nevertheless, we feel that our findings warrant particular attention, not least because they may pave the way both for prospective studies involving larger numbers of cases and for follow-up evaluations in the medium-long term.

CONCLUSIONS

The study suggests that this automated technique, which involves calculating independent nonlinear parameters, may constitute a noninvasive method for prediction of the results of EPS in patients with ventricular arrhythmias. This preliminary study has shown the good predictive value of nonlinear analysis techniques for this purpose, in that the results obtained correlate significantly with those of with programmed ventricular stimulation at EPS. However, further prospective studies are needed in order to verify the usefulness of this noninvasive tool for sudden death risk stratification in this kind of patients and to investigate the behavior of this analysis in function of physiological factors, such as autonomic regulation and heart rate.

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