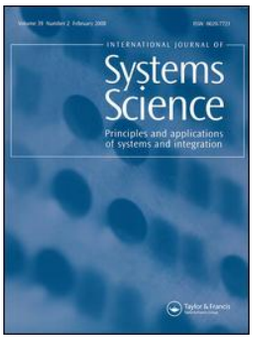

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Signal-analysis and a heuro-logistic interpretation of multi-lead electrocardiograms

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This paper describes a personal computer (PC) based analysis of multi-lead electrocardiograms (ECGs) and their interpretation employing an approach which is a combination of the two basic and conventional approaches, namely the heuristic approach and the logistic approach. The ECG analysis part of the software has been validated using the multi-lead ECGs of the common Standards in quantitative electrocardiography (CSE) database (Data Set 3). Using the spatial velocity approach, the analysis software reliably detects the QRS complexes and then the other component waves (i.e. P & T waves). More than 90% of the fiducial locations of various waves (i.e. P-on, P-off, QRS-on, QRS-off and T-end) estimated by the analysis software using this approach are found to be well within the tolerances recommended by the CSE. A successful attempt has been made to evaluate the parameters of diagnostic importance and interpret the multi-lead ECG analysis results using the heuro-logistic approach. The computerized interpretation thus made is found to be in agreement with the visual interpretation given by medical experts.

1. Introduction

Ever since the first attempts to automate ECG analysis by digital computer in 1957 (as reviewed by Pipeberger 1978), there have been many efforts by researchers to develop algorithms for ECG processing and interpretation through digital computers. The pioneering work of Caceres *et al.* (1962) led to the first program for conventional 12-lead ECG analysis. Nowadays, computerized ECG analysis is being utilized widely in many medical institutions. However, microprocessor-equipped ECGs are proliferating and are on the verge of widespread application in smaller hospitals, general practitioners' offices and the health screening environment.

As a result of the cooperative study 'Common standards for quantitative electrocardiography' (CSE project), summarized by Willems (1986), definite progress has been made since 1982 in the development of reference standards aimed at the evaluation of ECG measurement programs. Much research work is still going on in this area in a variety of disciplines: namely, assessment of the diagnostic performance of ECG-criteria, development of less sensitive criteria for wave measurement, the establishment of knowledge bases, the integration of ECG systems into larger departmentally-based consultation systems and so on. Thus, researchers are continuing their efforts towards improved methods of reliable and computer-based ECG interpretation systems so that, as a by-product of future cost-reductions and improvements in the computer technology, automatic ECG-analysis programs come into the hands of an ever-increasing number of medical users. In this current scenario, this paper aims at the propagation of the more effective auto-diagnostic protocol in ECG analysis.

The interpretation of the electrocardiogram (ECG) using computers often involves two major tasks: namely, the ECG signal analysis and disease classification. ECG signal analysis deals with the detection and measurement of various component waves with the aim of extracting those features of the ECG on which the disease classification is made. Conventionally, the disease classification task allocates a given ECG to one

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or more diagnostic categories using one of the two basic approaches, namely, the heuristic approach and the statistical approach. While the heuristic approach attempts to simulate the reasoning of the cardiologist, the statistical approach, on the other hand, employs multivariate statistical techniques for ECG interpretation. In the present work, a hybrid approach, which is a combination of heuristic and statistical approaches so as to derive the benefits of both approaches, has been applied.

The method has been successfully tested on the ECGs of Data Set 3 (DS-3) of the CSE database. It is a selected collection of multilead ECGs sampled at 500 samples per second simultaneously over 11 leads (i.e. I, II, V1-V6 and X, Y, Z). The other leads (i.e. III, aVR, aVL, aVF) were mathematically derived. The ECG interpretations provided by the software implemented on PC-AT are in agreement with those given by the medical experts. The validation of the software is discussed to demonstrate how well the ECG analysis software and the ECG interpretation software performed on the ECGs of a standard database and in the opinion of the medical experts, respectively. The paper concludes with a discussion.

2. ECG signal analysis

The objective of ECG signal analysis software is to extract all the primary parameters of ECG in every lead, such as the amplitude and duration of all the component waves, namely, P-wave, QRS complex, T-wave. Later, the secondary parameters—such as the interwave intervals, the frontal plane axis and so on, as required by a particular classification strategy—are derived from the primary ECG parameters.

The ECG signal analysis often commences with the detection of the QRS complex. A variety of ECG signal analysis programs have been reported in the literature with a recent one using artificial neural networks reported by Vijaya *et al.* (1997). A brief description of various QRS detection methodologies has also been presented in the paper. In the development of the software for the present work, it is assumed that the ECG signal has been acquired simultaneously over either the three orthogonal leads X, Y and Z or a minimum of three out of the standard 12-leads (namely I, II, III, aVR, aVL, aVF, V1–V6). The basic detection function employed is the spatial velocity (SV) function, one that has a band pass characteristic in the frequency domain, and which results from a second-order least square approximation of the first time derivative of each signal channel, as defined by Zywietz *et al.* (1990).

If $x_{i,k}$ is the amplitude of the ith sample in the kth lead, where i can be any integer between 1 and N ($N = 1000$, in the present work) and k can be any integer between 1 and L ($L = 12$, in the present work) then the spatial velocity (SV) is given by:

$$SV_i = \frac{1}{L}\left\{\sum_{k=1}^{L}[2(x_{i+2,k} - x_{i-2,k}) + 6(x_{i+1,k} - x_{i-1,k})]^2\right\}^{1/2}. \quad (1)$$

Figure 1 depicts, as can be seen from top to bottom, the ECGs over the leads V2, V1, III, II, I, respectively, of an ECG recording from the CSE Data Set 3 (Record No. 6) and the spatial velocity function (the bottom-most curve of the figure), as computed over all 12 leads using (1). It can be observed from the figure that the spatial velocity in the QRS region is very high compared with the iso-electric zones of the ECG signal. Thus, approximate locations of the onset and offset of a QRS complex are obtained using the SV function.

In the term defined by (1), the spatial velocity, besides not having the dimensions of velocity, has its spatial part basically refer to an average over 12 points of the anterior thorax. As a result of its bandpass characteristic in the frequency domain it has been successfully employed as the basic detection characteristic for the wave complex localization. Its use, as reported by Zywietz *et al.* (1990), avoids false positives in the QRS complex detection both in the presence of tall T-waves of pediatric ECGs and low voltage ECGs. While attempting to understand its bandpass characteristics, due consideration has to be given to the fact that, for the surface ECGs numerous researchers have calculated the frequency spectrum. Scher and Young (1960) have found the spectra in the range approximately, 0–170 Hz. It has also been established by them that, so as not to underestimate the ECG's upper frequency content, the ECG's length of time period be computed not from the repetition interval (heart rate) but from the cycle length P_{onset} to T_{end} or QRS_{onset} to T_{end}. These are not only some of the factors that have forced the choice of the function under the square-root of (1) but they have also contributed to the success in the correct identification and estimation of parameters of the QRS wave complex.

An identification of the base line is then taken up through a backward search from the QRS onset to a sample point, which is 0.3 s before the QRS onset, using a 0.04 s sliding window. A base level is identified as the signal level at an instant at which, for about 0.02 s on either side, the signal variation is very small. This is considered as the base level for all the QRS and T measurements. Following the recommendations of the CSE working party (1985), another base level is estimated in the T-P segment following the same criteria and it is considered as a base level for the P-wave measurements. However, an estimation of the base level for P-wave

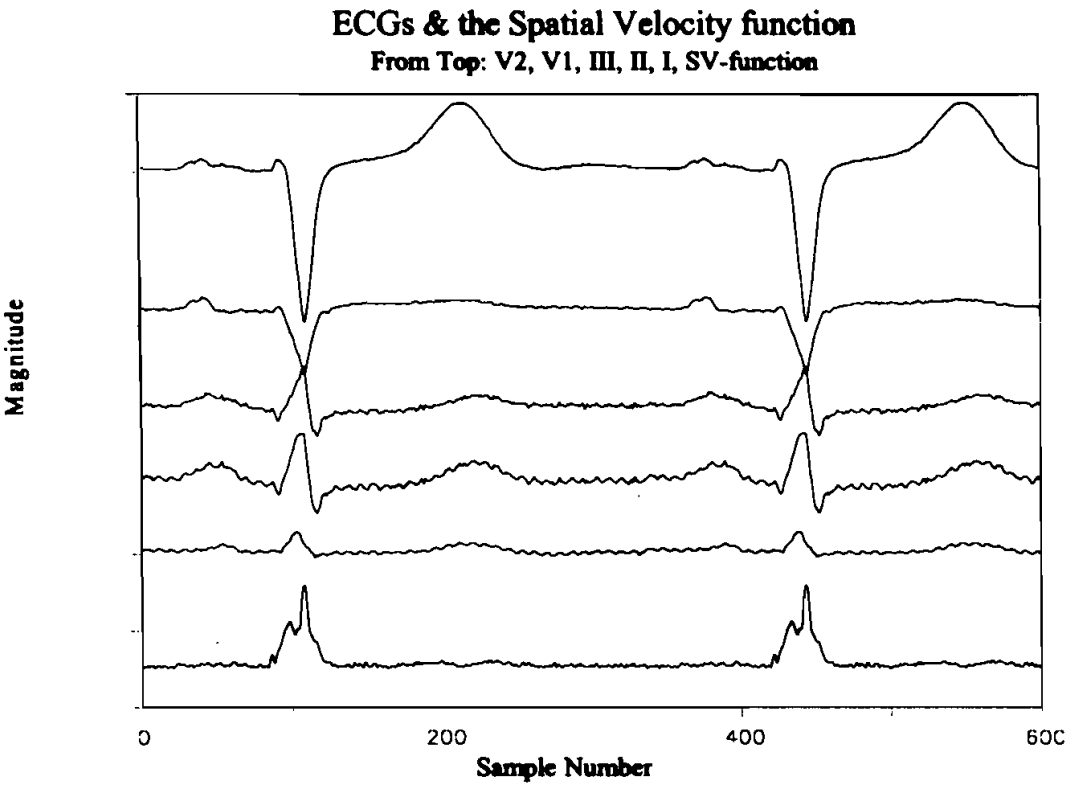

Figure 1. Spatial velocity function.

measurements is made only after identifying the P-wave, as described below.

To identify the P-wave, smoothed derivatives of voltage with respect to time, i.e. the linear velocity function, are derived in each lead using the following equation:

$$\text{linear velocity} \propto (x_{i+1} - x_{i-1}) \tag{2}$$

where i is as defined in (1) and is denoted as X_{I}, X_{II}, $X_{\mathrm{III}} \ldots$, corresponding to the leads: I, II, III and so on. It can be observed that the linear velocity term here is essentially the same as the slope of the ECG signal in the single lead under consideration, unlike the spatial velocity term which takes into account all 12 standard leads. The spatial velocity term in this context is computed as given below:

$$SV = \{(X_{\mathrm{I}}^2 + X_{\mathrm{II}}^2 + X_{\mathrm{III}}^2 + \cdots)\}^{1/2}. \tag{3}$$

Spatial velocity is computed for all points in a search region, which is between the previous ECG cycle's T-end and a point which is 8 ms before the present ECG cycle's QRS-onset. The point of maximum spatial velocity in the search region is noted as the P-peak. Threshold values of the spatial velocity, for use in identifying the P-onset and P-offset, are computed from 'quiet areas' at the beginning and end of the search region. P-offset is established by scanning backwards in time from the end-point of the search region. P-offset is detected as that point which, by itself, is less than the spatial velocity offset threshold, but is succeeded by eight consecutive points that exceed the offset threshold. P-onset is established during a region that commences at a point which is 156 ms preceding the P-offset and ends at the point of maximal linear velocity. P-onset is declared as that point which, by itself, is less than the spatial-velocity-onset-threshold but is preceded by a sequence of eight consecutive points that exceed the onset threshold. The 8-point sequence-length requirement is relaxed first to seven and then to six and so on to a minimum of 4, until the P-onset or P-offset is determined. If either P-onset or P-offset is still not found, or if the P-duration is computed to be less than 48 ms, a flag is set to signal the absence of a valid P-wave.

To detect and measure the parameters of a T-wave, a criteria similar to the one described above for the detection of the P-wave has been employed. The search region is chosen as the one in the interval between the QRS offset of the current ECG cycle and a point 8 ms before the P-onset of the succeeding ECG cycle.

In order to detect the J-point, a forward search has been carried out from the QRS offset towards the T-wave peak. The J-point (i.e. the junction of the QRS complex and the ST segment) marks the end of QRS. Thus, it is detected as a point of discontinuity in the slope of the terminal part of QRS complex. The terminal

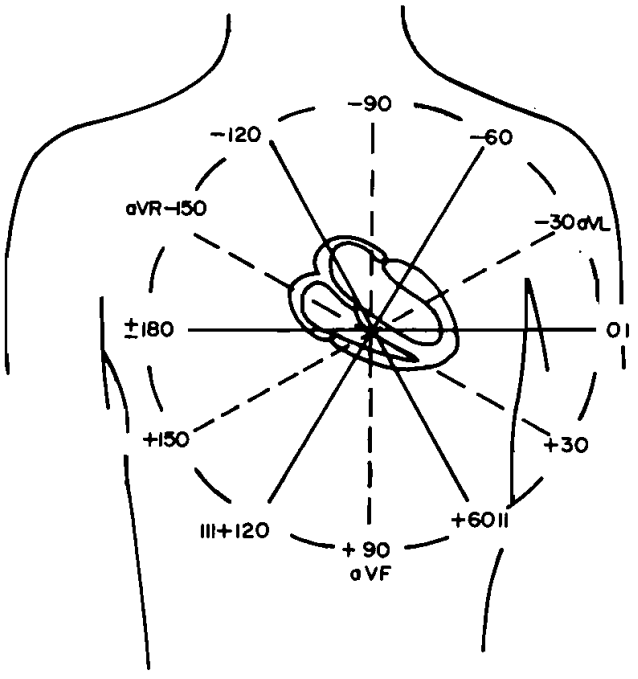

Figure 2. Hex-axial system.

part of the QRS complex is, quite often, a part of either the S- or R-wave. That is, the slope at $(J-1)$th point is much higher than that at the $(J+1)$th point.

The elevation or depression of the ST segment is found by measuring the signal level 40 ms beyond the J-point (i.e. at $J+40$) and comparing it with the base level.

The frontal plane axis is calculated based on the signal parameters in the two leads, i.e. lead I and lead II as given by Arzbaecher and Brody (1976). For example, considering the Einthoven traiangle as an equilateral triangle, the QRS axis can be computed as:

$$\text{QRS axis} = \tan^{-1}\left(\frac{2}{\sqrt{3}}\left[\frac{\text{net deflection in lead II}}{\text{net deflection in lead I}}\right] - 0.5\right). \quad (4)$$

If the net deflection in lead I is less than zero then the axis will be shifted by $\pi/2$, as shown in figure 2, so as to represent the right axis deviation, or else the deflection in lead aVF will decide the sign of the axis.

Thus, the ECG signal analysis program in the present work derives a number of ECG parameters, such as: R-R interval, heart rate, the amplitude of P, Q, R, S and T-waves and that of R′ or S′ waves (if present), the onset and the offset of P-wave, the QRS complex and the T-wave end, the QRS frontal plane axis and the corrected QT duration (QT_C), and the elevation/depression of the ST segment (i.e. that at 20, 40 and 60 ms from the J-point).

The flow chart shown in figure 3 depicts all the steps in extracting the features of a given ECG record. Before

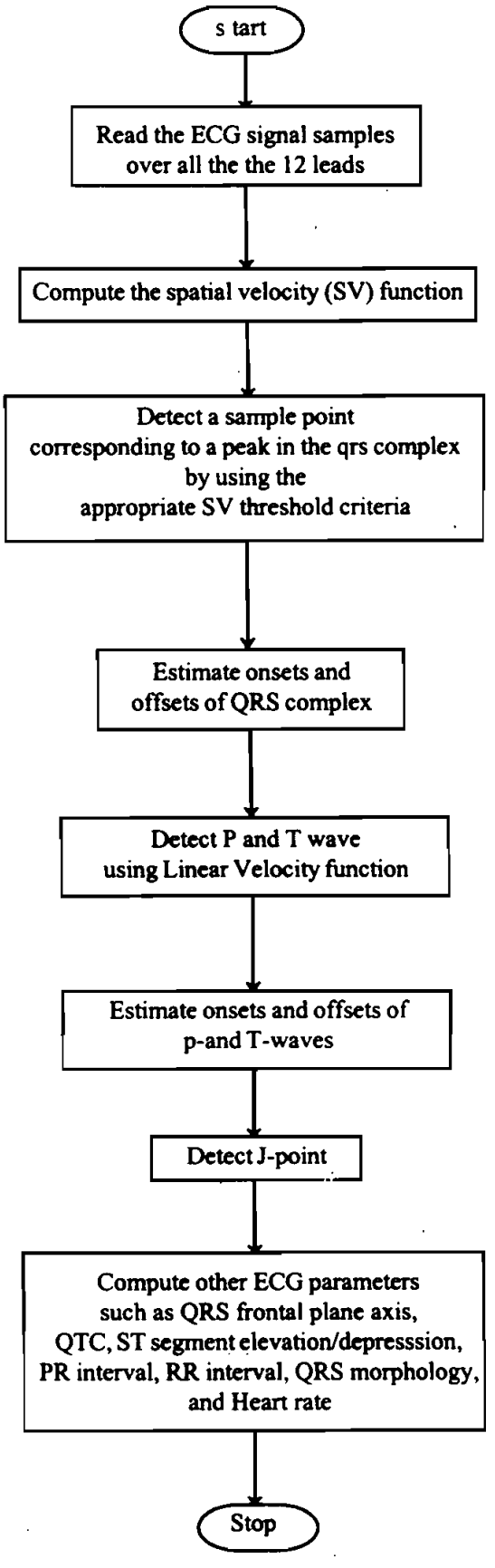

Figure 3. Flow chart for the extraction of ECG parameters.

attempting disease classification, the analysis software is successfully validated using all the ECGs of the CSE multilead measurement library (Data set 3) for which the human referee estimates of the wave fiducial points (namely, P onset, P offset, QRS onset, QRS offset and T end) are available. The validation results are described separately later.

3. Disease classification

The ultimate goal of almost every ECG analysis system is the classification of ECGs into various diagnostic categories. Since the early days of computer electrocardiography, one can observe that there are two basic approaches. In the first, the deterministic approach, cardiologists' methods of analysing ECGs are simulated, generally using decision-tree logic and conventional criteria, coded with the help of Boolean statements. In the second, the statistical approach, multi-variate statistical classification techniques are applied with the aim of improving conventional methods of ECG interpretation and minimizing the overall number of misclassifications. The most widely used classification model in this approach is based on the classical linear discriminant analysis (LDA) which assumes a normal distribution of the ECG variables in each of the disease classes. Since various ECG measurements show a skewed and far from Gaussian distribution, Willems and Lesaffre (1987) not only applied the LOG (logistic discriminant analysis) method, which does not assume any particular distribution, but also compared this method with the LDA technique.

In the present work, a heuro-logistic approach is employed to discriminate various ECGs into different diagnostic categories. Using the features extracted, as described in the previous section, the feature vector is constructed. The feature vector is then evaluated for each diagnostic category.

If $F = (1, f_1, f_2, \ldots, f_p)$ denotes the feature vector, in which $f_1, f_2, \ldots, f_p$ are a total of the p-features that constitute it, then, in what is known as the logistic approach by Kors and van Bemmel (1990), it is assumed that the posterior probability P for each feature vector would be of the form:

$$P(D_i) = \frac{\exp(\alpha_i)}{\sum_{j=1}^{G} \exp(\alpha_j)} \qquad (5)$$

where α is 1 plus the normalized probability of the disease class and is equal to $(\alpha_{0i}, \alpha_{1i}, \alpha_{2i}, \ldots, \alpha_{pi})$, and $\alpha_G = 0$; G denotes the number of diagnostic classes under consideration, and D_i denotes the ith diagnostic class.

The diagnostic classes are assumed to be exhaustive and mutually exclusive. Kors and van Bemmel (1990) reported that many distributions including multivariate normal distributions with equal and unequal covariance matrices satisfy this assumption. Estimates of the parameter vector α are supplied by a database of ECGs. The minimum probability of misclassification is attained by assigning an ECG to the category for which the posterior probability is largest.

Enhancement of diagnostic performance, less vulnerability to noise and measurement errors, and a flexible modification of diagnostic results, are some of the basic advantages of the multivariate statistical approaches of which the logistic approach described in (5) is a subclass. On the other hand, the requirement for a large database, a change in statistical parameters if used in other populations of patients, the absence of insight into measurements that contribute to diagnosis, the sensitivity of diagnosis to prior probabilities and ignoring physiological knowledge and interpretative experience, are the disadvantages of the multivariate statistical approach.

Due to the non-availability of access to a good ECG diagnostic database and to avoid several other inherent disadvantages, the authors employed a modified strategy of Maheshwari (1996) in which the heuristic knowledge provided by the skilled medical experts was used in the feature vector in the form of a multivariable matrix. As reported by Maheshwari (1996), Wagner (1994) and Okajima *et al.* (1990), this is based on the point scoring pattern, as is normally employed in the heuristic approach to disease classification. In the present work, the seven diagnostic classes considered are 'a normal ECG' and the broad variants of a couple of basic disease classes, namely (1) myocardial infarction (inferior, lateral or anterior), and (2) ventricular hypertrophy (left, right or bi-ventricular). The reader may refer to the medical terminology of Wagner (1994), given in the Appendix, to have a precise understanding about the diseases and their variants.

The clinicians widely use the point scoring pattern, described below, to arrive at the diagnosis while reading the ECGs. Point scores are obtained by summing the scores for the leads meeting the respective criteria. Every ECG is labelled with an appropriate diagnostic statement mentioned along with the point scoring pattern, given in tables 1, 2 and 3, depending on the total value of the point score.

The heuristic probability (α_i) of each diagnostic class is calculated by a point scoring algorithm. Its logarithmic function is then evaluated, and the posterior probability is evaluated using (5).

The CSE database contains recordings validated according to seven categories: namely, normal, left ventricular hypertrophy (LVH), right ventricular hyper-

Table 1. Scoring pattern for myocardial infarction (Okajima *et al.* 1990)

Position criteria	Anterior			Lateral			Inferior		
	V2	V3	V4	I	V5	V6	II	III	aVF
	(The numbers underneath denote point scores)								
$Q/R \geq 1/3$ & $Q \geq 36, 34, 32$ ms	3	3	3	3	3	3	3	2	3
$Q/R \geq 1/3$ & $Q \geq 28, 26, 24$ ms	2	2	2	2	2	2	2	2	2
$Q/R \geq 1/4$ & $Q \geq 24, 22, 20$ ms	1	1	1	1	1	1	1	0	1
−ve $T < -0.1$ mV	1	1	1	1	1	1	1	1	1

Threshold values for Q durations are aligned in the following order: criterion for adults aged over 18, for those aged 12–17, and for those aged below 11 years. Incidentally, 'abnormal Q-wave' instead of myocardial infarction is given as the interpretation if the criteria are fulfilled for those aged below 17.

If the total point score is:

≥ 8: definite infarction,
≥ 6: possibility of infarction,
≥ 4: cannot rule out infarction.

Table 2. Scoring pattern for left ventricular hypertropy (Okajima *et al.* 1990)

	Amplitude in millivolts	
RV_6	> 2.6, 3.0, 2.5, 3.0 or 2.5	3 points
RV_5	> 2.6, 4.0, 3.5, 4.0 or 3.5	3 points
R_{aVL}	> 1.2, 1.5, 1.5, 2.0 or 2.0	2 points
$R_{I,II,III,aVF}$	> 2.5	1 point
$\lvert Q_{V5}\rvert < \lvert Q_{V6}\rvert$ and Q_{V6}	< -0.5	2 points
$R_{V6} + \lvert S_{V1}\rvert$	> 3.5, 5.0, 4.0, 5.0 or 4.0	3 points
$R_{V5} + \lvert S_{V1}\rvert$	> 3.5, 6.0, 5.0, 6.5 or 5.0	2 points
R_I	> 1.5, 2.0, 2.0, 2.5 or 2.5	2 points
$-30° \geq$ axis $> -90°$		1 point
$-5° \geq$ axis $> -30°$(< 11 years)		1 point

The threshold values for voltages mentioned are aligned in the following order: threshold for adults, boys aged 12–18 years, girls aged 12–18 years, children aged 3–11 years and children under 2 years respectively.

High voltage (left ventricle): total points = 4 or 5.

Possible left ventricular hypertrophy: total points > 6.

Definite left ventricular hypertrophy: total points > 4 in addition to abnormal ST-T on leads V5 and V6, or $R > 4.0$ (4.5, 4.5) 5.0, 5.0 mV (V5, V6)

Table 3. Scoring pattern for right ventricular hypertropy (Maheshwari 1996)

axis > 90°		Begin scoring
axis > 110°		3 points
R_{V5} or R_{V6}	> 2/6 mV	3 points
R_I, R_{II}, R_{III} or R_{aVF}	> 2/5	1 point
R_{V1} or R'_{V1}	> 0.5(2.0, 1.5)2.0, 2.0 mV	2 points
ST depression > 0.2 & $T < -0.1$ (V1, V2, V3)		1 point each
$Rv_4 < S/2$ and $R > 0$ mV (V4)		1 point
$R/S <$ or $R < 1.5$ mV (V5, V6) or $S < -1.5$ mV (V5, V6)		2 points

The threshold values for voltages mentioned are aligned in the following order: threshold for adults, boys aged 12–18 years, girls aged 12–18 years, children aged 3–11 years and children under 2 years respectively. The RVH is not indicated if there is MI or Complete or incomplete RBBB (see the Appendix).

Definite hypertrophy if the score is	≥ 8 points
Possible hypertrophy if the score is	≥ 6 points
Cannot rule out hypertrophy if the score is	≥ 4 points

trophy (RVH), bi-ventricular hypertrophy (BVH), anterior myocardial infarction (AMI), inferior myocardial infraction (IMI) and combined infarction (MIX), as explained by Willems (1990). So, all such ECGs that cannot be classified into one of the six disease categories are labelled as 'Normal' ECGs.

This classification methodology has been successfully implemented in software as depicted in the flow chart shown in figure 4. The ECGs in Data Set-3 of the CSE database are subjected for a disease classification using this heuro-logistic approach and the classifications made by the software are successfully compared with the diagnostic opinion of the medical experts.

4. Software validation

This section mainly deals with the validation of the ECG analysis part through a comparison of the software estimated parameters namely: P_{onset}, P_{offset}, QRS_{onset},

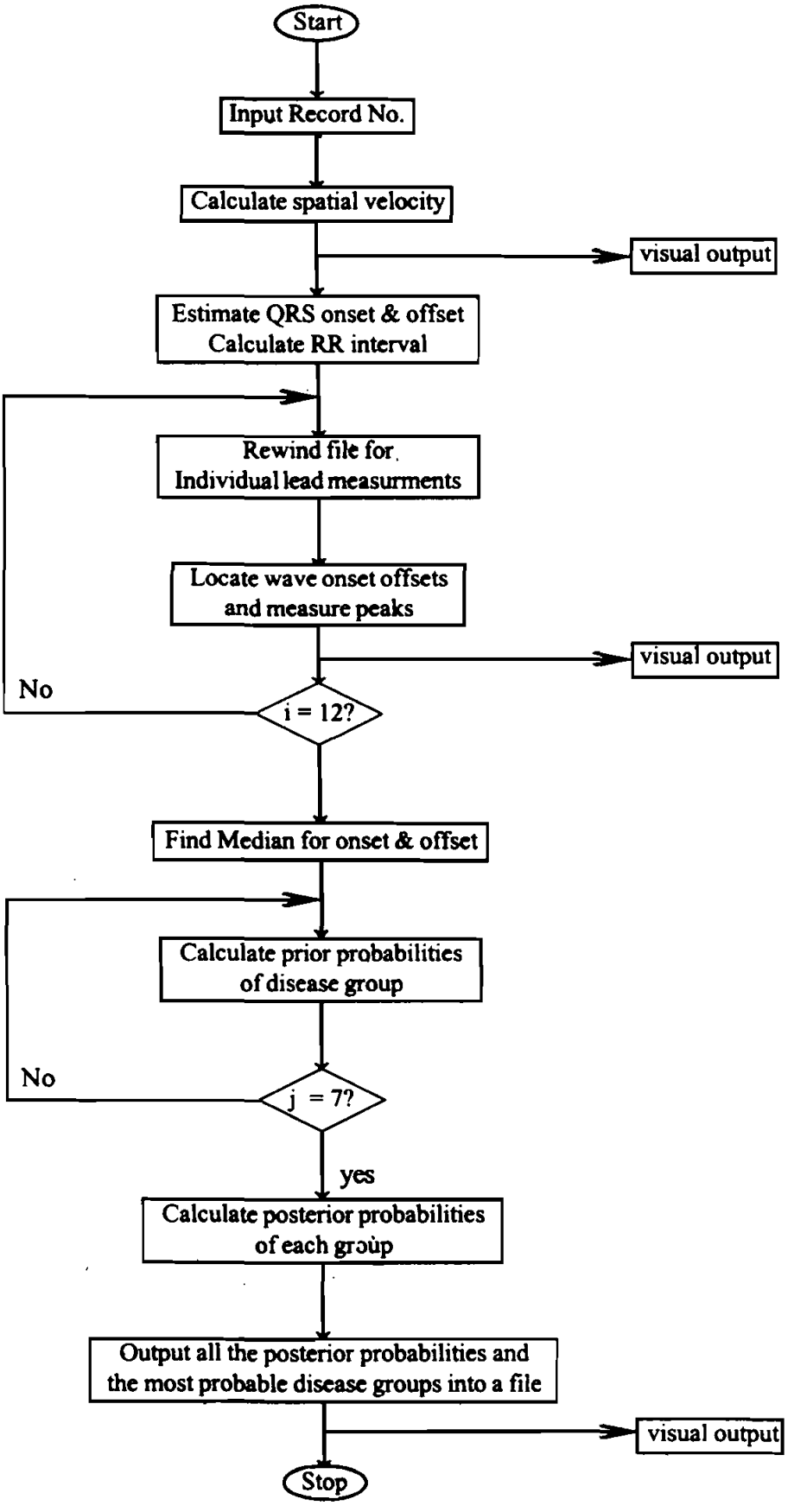

Figure 4. Flow chart depicting the implementation of both the ECG signal analysis and the ECG interpretation algorithms.

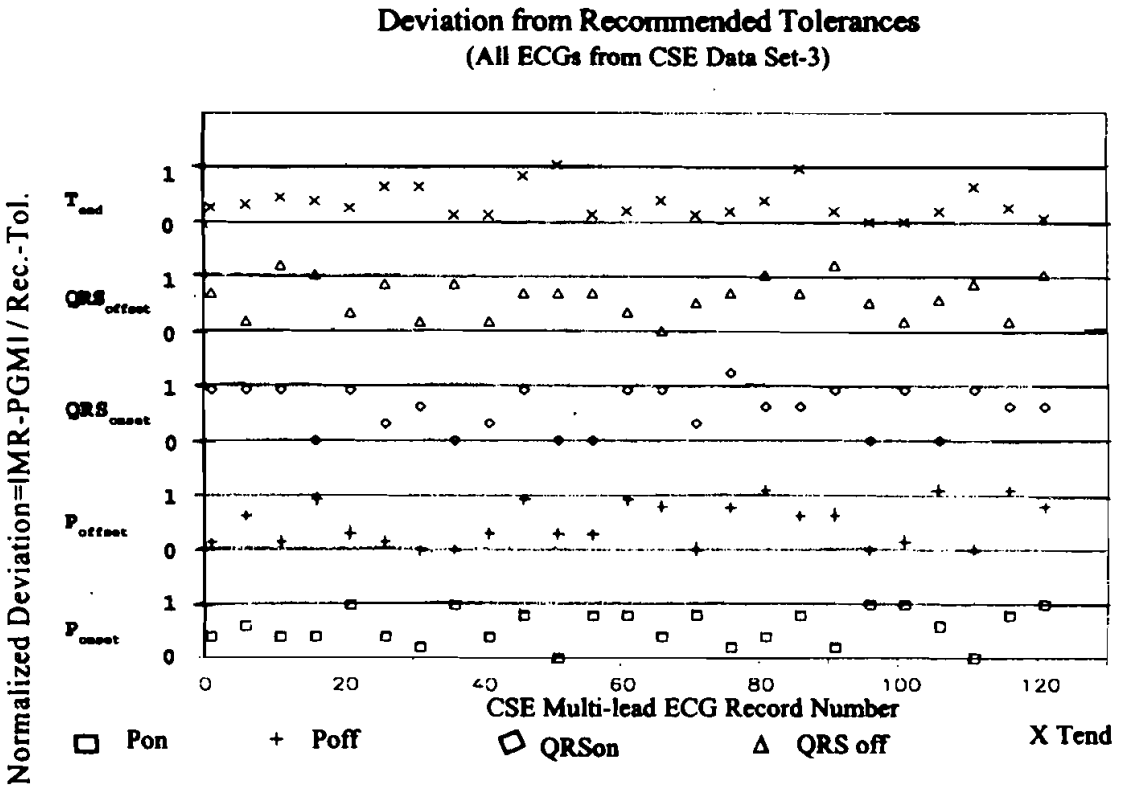

Figure 5. A graph summarizing the results of ECG analysis software's validation.

QRS_{offset} and T_{end} with the corresponding estimates given by the expert ECG readers of the standard ECG database. In addition, this section also includes the authors' efforts to validate their program's assignment of an ECG into one of the specific clinical diagnoses.

The software developed for the ECG signal analysis and the disease classification was validated using all 125 ECG records of the CSE database (Data Set 3) which has a collection of ECGs representing a variety of pathological events. All the ECGs of this database are acquired simultaneously using a uniform sampling interval of 2 ms and with a minimum resolution of 5 μV while converting the analogue ECG to digital data (10-bit ADC), as specified by Willems *et al.* (1990).

The five-wave fiducials, namely, P-onset, P-offset, QRS-onset, QRS-offset and T-end as obtained by the human referees are supplied for every fifth record (as reported by Willems 1988 on CSE data Set 3) which contain a total of 125 ECGs. Using the ECG signal analysis software, for every fifth ECG of the database, all five measurements are made and are compared with the median of those provided by five human referees of the database. It is found that more than 90% of the program's measurement estimates are well within the admissible deviations recommended by The CSE Working Party (1985). Table 4 shows a comparison of the program estimates (symbolized as 'Pgm') of the typical ECG fiducials: P-onset, P-offset, QRS-onset, QRS-offset, T-end with the corresponding median (symbolized as 'MR') of the estimates of five CSE referees. At the end of the table are given the recommended tolerances (Rec. Tol.), i.e., the CSE recommended average standard deviations of these five ECG fiducials in milliseconds (ms) as cited by The CSE Working Party (1985). The results are further depicted in figure 5.

The ECG signals of the CSE database are digitized using a uniform sampling interval of 2 ms. So, a recommended tolerance of 10.2 ms, for P-onset, would mean that a difference of $\cong 5^{+}$ sample positions between the statistical median of the five referees' estimate and the program's estimate is admissible. It may be noted from the table that, in Record Nos 21, 31, 56 and 66, all five fiducial locations, namely, P-onset, P-offset, QRS-onset, QRS-offset and T-end as estimated using the methodology described in this paper, are well within the recommended tolerance limits from their respective median referee values.

Thus, in a total of 125 measurement estimates reported in table 4, over 90% of the program's estimates are well within the recommended tolerance limit. This can be easily verified from figure 5. The figure shows the normalized deviation of the parameters, namely P_{onset}, P_{offset}, QRS_{onset}, QRS_{offset} and T_{end} for all the CSE Multi-lead ECG records for which the visual

Table 4. Typical results of the ECG analysis software

Record	P-onset		P-offset		QRS-onset		QRS offset		T-end	
No.	MR	Pgm	MR	Pgm	MR	Pgm	MR	Pgm	MR	Pgm
1	22	24	87	86	139	136	202	198	370	366
6	22	19	74	70	87	84	129	130	270	265
11	22	20	77	78	97	94	145	138	281	288
16	35	33	86	80	102	102	144	138	283	289
21	105	100	164	162	181	178	233	231	420	416
26	40	38	99	100	141	140	225	220	365	355
31	38	37	100	100	124	122	173	172	311	321
36	53	48	106	106	124	124	185	184	320	322
41	56	54	106	104	127	126	193	192	340	342
46	26	22	80	74	104	100	172	168	340	327
51	13	13	68	66	90	90	135	131	246	262
56	78	74	132	134	170	170	218	214	391	393
61	53	49	123	120	165	168	210	208	366	363
66	63	61	120	115	137	140	190	190	353	347
71	44	41	97	97	119	118	161	157	301	299
76	35	36	99	104	124	128	199	195	320	323
81	40	42	100	93	122	120	180	174	326	332
86	38	41	94	90	120	118	186	193	370	355
91	36	35	96	92	116	113	175	182	331	334
96	21	26	79	79	142	142	201	198	340	340
101	24	19	76	75	93	90	134	133	268	268
106	65	62	120	113	130	130	177	174	346	349
111	–	10	–	80	96	93	145	140	307	297
116	50	46	109	102	120	118	163	162	314	318
121	25	20	85	98	124	122	182	176	325	326
Rec. Tol.	10.2 ms		12.7 ms		6.5 ms		11.6 ms		30.6 ms	

Pgm: Program estimated fiducial location (in sample numbers)
MR: Statistical median of five human referees' fiducial estimates

estimates are known. The parameter on the ordinate of the graph is a normalized deviation of a parameter (say, P_{onset}). That is, a parameter's deviation (i.e. $|MR - Pgm|$) from the median value of the visual estimates provided by the human ECG readers of the CSE database, is normalized with respect to the recommended tolerances of the measurement standards, given by The CSE Working Party (1985). It can be observed from the graph that estimation of the program's estimate of the parameters P_{offset}, P_{onset}, QRS_{onset}, QRS_{offset} and T_{end} are well within the recommended tolerances except in the case of three records for P offset, a record each for QRS_{onset} and QRS_{offset}. Through a look at the table, it can be observed that in all three records, namely: 81, 106 and 116, P_{offset} deviates by 1.3 ms more than the specified tolerance band (i.e. the band between 0 and 1 of the graph). A similar observation reveals that while the estimation of the QRS onset in record number 76 deviates by 1.5 ms, that in the QRS offset in record number 86 deviates by 2.4 ms. The fact that the deviation from a specified tolerance band of the graph does not occur in all the parameters of a given record reveals that the reasons for their deviation are purely subjective, and thus record dependent. Out of a total of 125 fiducial location estimates (i.e. five fiducial locations in each of the 25 ECG records) just five estimates deviate from the tolerance band by about one sampling interval (i.e. 2 ms), hence it does not significantly affect the estimation of diagnostically significant parameters of the ECG analysis. Thus, the algorithm's estimation is well within the tolerance band in 96% of the estimates.

The diagnostic interpretation of the ECGs of the CSE database is not yet disclosed. In the absence of the CSE diagnostic codes of these ECGs being used in the present work, the authors sought the help of local medical experts for the diagnostic interpretation of the ECGs so as to enable the validation of the disease classification part of the software. It is found that the ECGs interpreted by this software, in respect of the diagnostic classes namely, IMI, AMI, LVH, RVH and Normal were in agreement with the interpretation of the local

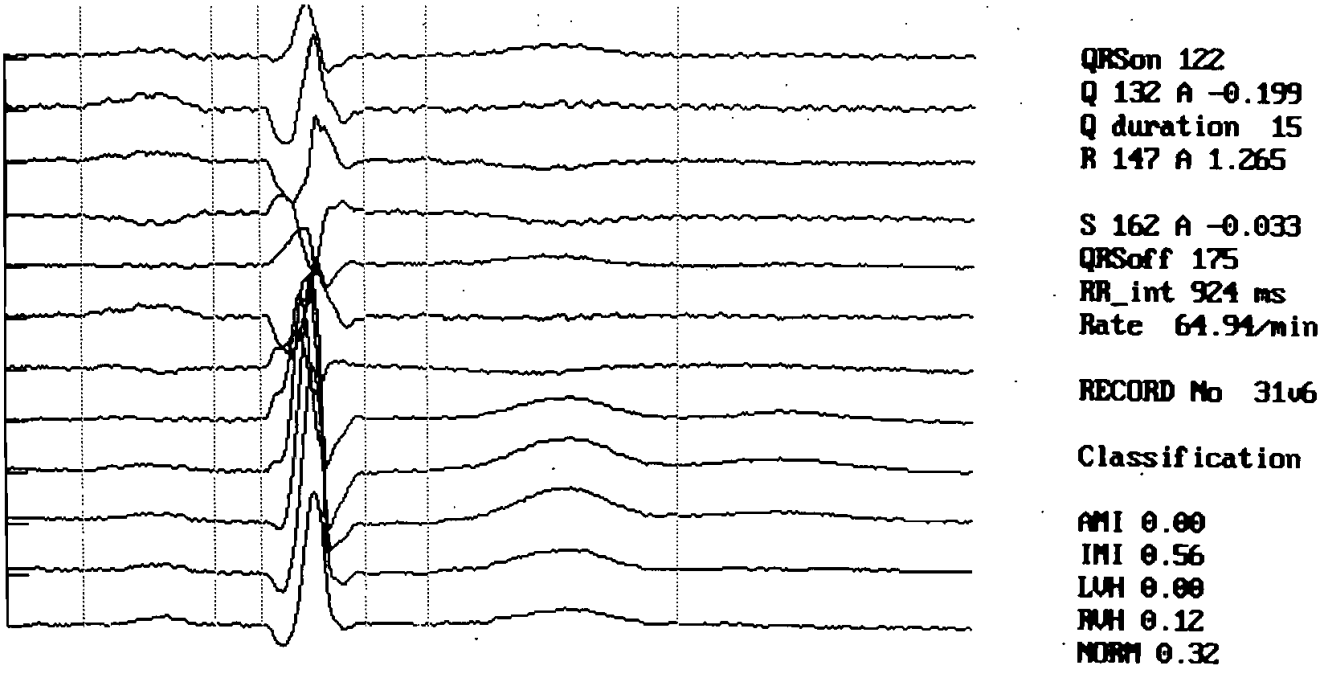

Figure 6. Output of the software for Record No. MA_031.DCD.

medical experts. An example interpretation provided by the ECG interpretation software is shown in figure 6. The figure shows the ECG tracing for one cycle over all 12 leads with the ECG at the top corresponding to lead-I and that at the bottom corresponding to lead-V6 in the order I, II, III, aVR, aVL, aVF, V1, V2, V3, V4, V5 and V6. On the right side and the bottom of the ECG tracing, along with the details such as the position of the Q, R, S wave in terms of the sample number within the ECG cycle shown, typical parameters such as heart rate, R_R interval, typical global fiducials (P-on, P-off and so on) and the QRS axis are also mentioned. The probable diagnostic statement as arrived at by the software is mentioned along with the values of the posterior probabilities for the diseases under consideration. This is one of several ECGs in which the program's interpretation has coincided with that of the medical experts.

5. Discussion

The accuracy of the diagnostic statement improves when it is made on the basis of ECGs acquired simultaneously as against that based on the ECGs acquired sequentially over several leads. This viewpoint has been verified by a number of researchers who were involved in the development of the CSE ECG database. The present authors employed spatial-velocity based ECG signal analysis, which assumes the ECG data have been acquired simultaneously over at least three leads, thus leading to an improved detection of various component waves and a higher accuracy in the measurement of corresponding wave fiducials.

The heuristic approach to ECG classification is directly based on knowledge from cardiologists, irrespective of whether one uses a decision tree or fuzzy classifiers. So, the highest accuracy of the diagnostic statement attainable can at most be that of cardiologists. On the other hand, the motivation for using the statistical methods is to surpass the interpretation accuracy limit to a value beyond that attainable by the best human interpreter. But this is only possible when the statistical classifier has been constructed using a database, consisting of a large number of ECGs for every diagnostic category, and in which every ECG has been validated by ECG-independent evidence.

In the present work, heuristic knowledge provided by skilled medical experts has been used in the feature vector of the logistic approach in addition to the use of a multivariable matrix that represents the scoring pattern, as in the heuristic approach. This hybrid approach has been employed in the classification methodology due to the non-availability of access to a diagnostic database. The program's interpretation is found to be in agreement with those of the medical experts in respect of all the diagnostic categories selected in the present work.

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Appendix

Axis: Direction of an ECG waveform in the frontal plane measured in degrees.

Anterior: Located towards the front of the body.

Superior: Situated above and closer to the head than another body part.

Inferior: Situated below and closer to the feet than another body part; the opposite of superior.

Lateral: Situated toward either the right or left side of the heart or of the body as a whole.

Precordial: Situated on the thorax, directly overlying the heart.

Endocardium: The inner aspect of a mycardial wall adjacent to the blood filled cavity.

Epicardium: The outer aspect of a myocardial wall adjacent to the pericardial lining that closely envelopes the heart.

Left-Bundle-Branch-Block (LBBB): Partial or complete failure of conduction in the left bundle branch of the ventricular purkinje system.

Right-Bundle-Branch-Block (RBBB): Partial or complete failure of conduction in the right bundle branch of the ventricular purkinje system.

Complete bundle branch block: Total failure of conduction in the right or left bundle branch; defined by QRS duration > 0.12 s with RBBB and > 0.14 with LBBB.

Incomplete bundle branch block: Partial failure of conduction in the right or left bundle branch; defined by QRS duration of 0.10–0.11 s with RBBB and 0.11–0.13 s with LBBB.

Hypertrophy: Increase in muscle mass; most common in the ventricles when compensating for pressure or systolic overload.

Infarct: An area of necrosis (i.e. the death of a piece of bone or tissue) in an organ resulting from an obstruction in its blood supply.

Ischemia: an insufficiency of blood flow to an organ which is so severe that it disrupts the function of the organ; in the heart it is often accompanied by precordial pain and diminished contraction.

Aerobic metabolism: The intra-cellular method for converting glucose into energy which requires the presence of oxygen and produces enough energy to nourish the cell and also to cause it to contract.

Anaerobic metabolism: The intra-cellular method for converting glucose into energy which does not require oxygen, but produces only enough energy to nourish the cell.

Myocardial ischemia: Reduction in the supply of oxygen below the amount required by the myocardial cells to maintain aerobic metabolism.

Myocardial infarction: Death of myocardial cells as a result of failure of the circulation to provide oxygen to restore metabolism after the intra-cellular stores of glycogen have been depleted.

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