Cardiac Infarction Injury Score: An Electrocardiographic Coding Scheme for Ischemic Heart Disease

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SUMMARY A multivariate decision-theoretic electrocardiogram (ECG) classification scheme called Cardiac Infarction Injury Score (CIIS) was developed using ECGs of 387 patients with myocardial infarction (MI) and 320 subjects without infarction. The most accurate and stable classification was achieved by using a combination of eight binary (single threshold), three ternary (two thresholds), and four ECG features measured on a continuous scale. For practical visual coding of ECGs, the CIIS coding procedure uses a checklist containing 12 items measured from the conventional 12-lead ECG.

The CIIS test results indicate that, in comparison with conventional ECG criteria for MI used in clinical trials, the diagnostic accuracy can be considerably improved by optimizing feature and threshold selection and by multivariate analysis. The CIIS detected MI with a sensitivity of 85% and a specificity of 95%. Using a higher severity level, a specificity of 99% was achieved, with a sensitivity of 71%. One of the primary uses of the CIIS is coding of significant worsening of the ECG with new coronary events from annually recorded ECGs in clinical trials and epidemiologic studies.

RELIABLE DETECTION of myocardial infarction at periodic follow-up examinations and reliable identification of the progression or regression of cardiac involvement in hypertension are major concerns in epidemiologic studies and clinical trials aimed at preventing heart disease. Although improved non-invasive techniques may replace or supplement electrocardiography in detecting and grading the severity of left ventricular hypertrophy in hypertension, the ECG remains the most important tool for detecting and classifying myocardial infarction.

The Minnesota Code has become the most widely used ECG classification system in epidemiologic studies, and its application significantly improved standardization of ECG measurements. The Minnesota Code is a hierarchical, decision-tree type of ECG classifier that was developed by determining upper normal limits for univariate or bivariate distributions of selected ECG features, particularly in the design of category 1 of the code (Q, QS waves and related items). Problems are encountered with this approach if many features are used in classification criteria. When the Minnesota Code was developed, statistical computer techniques were not in general use and the criteria (features and thresholds) were selected more or less intuitively, causing two major problems: first, the feature selection and the thresholds are not optimal and the sensitivity of the criteria tends to be low; second, the use of a decision-tree structure results in a considerable degree of classification instability, whereby a single error can easily result in misclassification.

The Cardiac Infarction Injury Score (CIIS) scheme was developed to improve the accuracy and stability of ECG classification in ischemic heart disease. The CIIS classifier uses a set of 11 discrete (binary and ternary) ECG features in combination with four features measured in continuum and uses a simple scoring scheme suitable for both visual and computer classification of the conventional 12-lead ECG.

Methods

ECG Data Files Used for Program Design and Testing

The data file used to design CIIS was composed of the ECGs of 387 patients with myocardial infarction and 320 subjects without clinical evidence of infarction (table 1). The criteria for infarction were based on non-ECG evidence in the acute phase, including prolonged, typical cardiac ischemic chest pain not relieved by nitroglycerin, and a peak CPK enzyme level more than 85% above the upper normal limit for the hospital. The noninfarct group consisted of 145 subjects with documented hypertension of over 1 year's duration (diastolic pressure 90 mm Hg or higher) but without any clinical evidence of myocardial infarction and 175 ostensibly healthy subjects with a normal blood pressure. The age range for the patients with myocardial infarction was 30–76 years, (median 58 years). The age range for the noninfarct group was 19–75 (median 42 years).

The source data used in ECG analysis were composed of digital tapes acquired at a sampling rate of 500 samples/sec per channel. The overall frequency band of the data acquisition system was 0.05–125 Hz (lower and upper 3 db points).

Two-thirds of the ECG data file was randomly assigned to the design (training) set and the remaining third was retained to test the accuracy of the CIIS.
classifier (table 2). After test results were obtained on this independent test subgroup, the final refinement of the thresholds and the determination of the coefficients for the linear discriminant function were performed using the whole data file.

The repeatability of the CIIS was tested in a different group of 139 male subjects, ages 35–57 years, in whom the ECG was rerecorded within 8 weeks from the first ECG. These subjects had no clinical evidence of myocardial infarction, but about one-third of them had hypertension. These subjects were recalled for an exercise test and had no clinical events in the interim period. This test group was used to assess normal confidence limits of CIIS changes (table 3) when coding events signaling significant worsening of the ECG in serial ECG comparison.

**Statistical Methods**

**Feature Selection**

The initial set of ECG features used to develop CIIS contained a set of 32 logic criteria for myocardial infarction used in the Minnesota Code and a supplementary set of variables listed in table 4. Initial test runs revealed, however, that both the features used and the thresholds assigned to the Minnesota Code variables were suboptimal and these features rarely, if ever, entered into the best set of 14 for the infarction vs noninfarction classifier. Therefore, the logic criteria of the Minnesota Code were rejected and the search was limited to the variables listed in table 4.

The first 10 features of table 4 were used as both discrete and continuous variables. The procedures used for feature “discretization” have been described. These procedures aim at optimizing the threshold selection either at binary (a single threshold) or ternary level (high and low threshold) to maximize the classification accuracy. The feature selection was done by the conventional forward sequential selection (“step-up”) algorithm using the Mahalanobis distance as the optimization criterion. In instances when the binary and the ternary level “discretization” yielded equal performance, the lowest quantization level (i.e., binary) was retained.

For calculation of the Mahalanobis distance and the linear discriminant function, the Gauss-Jordan method of matrix inversion described by Orden was used with double-precision (64-bit) arithmetic.

**Selection of Lead and Format for CIIS**

The CIIS was designed for the conventional 12-lead ECG. For feature selection (such as the Q-wave duration), two “redundant” leads were also used: the inverted aVR (aVR) and the inverted aVL (aVL) lead. These inverted leads fall into a smooth, continuous logical pattern sequence within other conventional frontal plane leads. The initial R wave in aVL turned out to contain diagnostic information usually ignored by current ECG classification criteria. This information is presented in a more familiar form as a Q wave in the inverted lead aVL. Similarly, the R and

<table>
<thead>
<tr>
<th>Feature set</th>
<th>Design file</th>
<th>Test file</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SP (%)</td>
<td>SE (%)</td>
</tr>
<tr>
<td>A. Discrete features</td>
<td>90</td>
<td>95</td>
</tr>
<tr>
<td></td>
<td>96</td>
<td>93</td>
</tr>
<tr>
<td></td>
<td>98</td>
<td>82</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>62</td>
</tr>
<tr>
<td>B. Continuous features</td>
<td>90</td>
<td>93</td>
</tr>
<tr>
<td></td>
<td>96</td>
<td>88</td>
</tr>
<tr>
<td></td>
<td>98</td>
<td>85</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>62</td>
</tr>
<tr>
<td>C. Mixed discrete and continuous features</td>
<td>90</td>
<td>97</td>
</tr>
<tr>
<td></td>
<td>96</td>
<td>94</td>
</tr>
<tr>
<td></td>
<td>98</td>
<td>88</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>71</td>
</tr>
</tbody>
</table>

The classifier discriminant score was adjusted to yield a specificity of 90, 96, 98 and 100% in the design set.

Abbreviations: SP = specificity (fraction of correctly classified true negatives [i.e., noninfarcts]); SE = sensitivity (fraction of correctly classified true positives [i.e., infarcts]); AI = association index (SP + SE – 100).
The amplitudes are measured in standard millimeters (1 mm = 0.1 mV). Absolute values of negative amplitudes are used. The T amplitude (positive and negative phase) is measured as the absolute value of the largest deflection above and below the PR baseline in a window spanning from 80 msec after the end of QRS to the end of T (see appendix).

CIIS severity levels: level A, CIIS 20, probable injury; level B, CIIS 15, possible injury; level C, CIIS 10, borderline abnormality.

T waves in \(-aV^R\) appeared to improve the diagnostic accuracy of the classifier.

In the course of the CIIS development efforts, it also became apparent that the grouping of ECG leads for the Minnesota Code and other clinical ECG classification criteria is suboptimal. The same thresholds and logic criteria are traditionally used for diverse groups of leads, such as I, aVL, V6 (lateral), II, III, aVF (inferior) and \(V_1\) to \(V_5\) (anterior), even though the directions of the lead vectors of the leads in each group may differ widely. In the CIIS, only ECG leads that had a spatial angle less than 20° between their lead vectors were grouped together, i.e., I and \(V_6\), II and aVF, III and \(-aV_L\). The largest value of a given amplitude and duration in each pair was chosen for analysis. The remaining 7 leads were used individually (aVL, \(-aV_R\), \(V_1\), \(V_2\), \(V_3\), \(V_4\) and \(V_5\)).

### Table 3. Simplified Cardiac Infarction Injury Score (CIIS) Classifier for Practical Visual Coding of Electrocardiograms

<table>
<thead>
<tr>
<th>Component Lead</th>
<th>Feature</th>
<th>Threshold score</th>
</tr>
</thead>
<tbody>
<tr>
<td>aVL</td>
<td>Q duration in seconds (measured to nearest threshold)</td>
<td>Q absent 5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.010 1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.020 3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.030 9</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.040 10</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.050 12</td>
</tr>
<tr>
<td>aVL</td>
<td>T amplitude in mm if T negative add 2 points for each mm</td>
<td>≤ 0.5 or 3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>≥ 3</td>
</tr>
<tr>
<td>-aVR</td>
<td>R amplitude in mm = R (subtract 1 point for each mm)</td>
<td>−1 −R</td>
</tr>
<tr>
<td>aVL</td>
<td>T amplitude (positive phase) in mm. Subtract 2 additional points for each mm exceeding 4</td>
<td>0 6</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1 3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2 0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3 −2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4 −5</td>
</tr>
<tr>
<td>III, aVF</td>
<td>Largest Q/R amplitude ratio</td>
<td>≥ 1/20 12</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.040 5</td>
</tr>
<tr>
<td>III</td>
<td>T amplitude (negative phase) in mm</td>
<td>&gt; 1 5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>&gt; 2 5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>&gt; 3 or 5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>≥ ½ 5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>&gt; 1/20 9</td>
</tr>
<tr>
<td></td>
<td></td>
<td>&lt; 2 5</td>
</tr>
</tbody>
</table>

Each of the first 10 features of Table 4 were measured from 10 leads or lead sets, yielding 100 features. Features 11, 12 and 13 (Table 4) increased the total set of variables to 103. In the final refinement of the CIIS classifier (Table 5), positive and negative portions of the T wave (whenever biphasic) were treated as separate variables to simplify the logic for visual coding.

### Results

Extensive empirical studies during the development of the CIIS indicated that the best feature subsets were usually obtained when the feature selection was done on the continuous rather than the discrete features, particularly when a high level of specificity was desired. Therefore, we chose the feature set for CIIS using the features listed in Table 4 as continuous variables. It turned out that the discrete features chosen this way perform about as well as the continuous features (Table 2). However, a further improvement at a high level of specificity is achieved by using a combination of continuous and discrete features (set C of Table 2).

Table 5 gives the coefficients of the linear discriminant function for the CIIS with 15 combined discrete and continuous features. Three of the features appear both as continuous and discrete variables (1 and 10, 6 and 11, 8 and 12, respectively), because unequal, non-linear weights in different feature regions can occasionally improve classification accuracy.

Although continuous features are usually awkward in visual ECG coding, the scoring scheme was simplified by incorporating the four continuous features within the structure of the discrete features (Table 3). There are 12 steps in this scoring scheme: five involve T-wave measurements, four involve Q-wave durations or Q/R amplitude ratios, two involve the R-wave amplitude and one involves the S-wave amplitude.
The T- and R-wave amplitudes of the inverted lead $-aV_R$ played a surprisingly prominent role in selection of features for the CIIS classifier, always ranking very high among the best features and their combinations in the linear discriminant. In Table 5, the features are listed in the order they were selected to the best discriminating combination, whereas in Table 3, the features are grouped according to the logical sequence of frontal and horizontal plane leads.

### CIIS Severity Levels

In practical applications, it is often desirable to "discretize" the continuous index such as the CIIS at two or three levels of confidence or the likelihood of the abnormality. The severity levels for CIIS in Table 3 were adjusted so that specificity levels of 90%, 96% and 98% were consistently maintained both for the design and the test sets. The validity of these limits was further investigated in 139 subjects in whom the recording was repeated within 8 weeks after the first ECG, with no evidence of coronary events in the interim period. A worsening of the CIIS exceeding 10 points was observed in 4% and a worsening exceeding 20 points in 1% of the subjects. It thus seems plausible to propose these same CIIS severity levels at least tentatively for coding of significant worsening of the ECG in serial comparison of successive annually recorded ECGs in clinical trials.

### CIIS Performance According to the Age and Location of Infarct

We estimated the extent to which the accuracy of the CIIS depends on the age and the anatomic location of the infarct (Table 6) and found that the age of the infarct influences the accuracy less than expected. The CIIS performs best on infarcts that are 1 week to 1 month old. However, even in patients whose infarct is more than 1 year old, the sensitivity remains at 80% for the 98% specificity level. The CIIS performance is fairly uniform for lateral, anterior and posterior locations of the infarct. As expected, the performance is worse whenever visual classification of the postevent record regarding the location was uncertain.

Figure 1 is a sample ECG tracing illustrating the CIIS coding procedure following the sequence of items in Table 3. More detailed guidelines are given in appendix 1. Figure 2 is a second example of ECG features contributing to CIIS in an old infarction classified in the acute phase as posterior-diaphragmatic.

### Table 5. The Cardiac Infarction Injury Score Classifier with Eight Binary, Three Ternary and Four Continuous Features

<table>
<thead>
<tr>
<th>Feature</th>
<th>Lead</th>
<th>Quantization level</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. T amplitude (positive phase) ($\mu$V)</td>
<td>$-aV_R$</td>
<td>Continuous</td>
<td>-0.0262</td>
</tr>
<tr>
<td>2. Largest Q:R amplitude ratio</td>
<td>II, aV_F</td>
<td>Binary</td>
<td>11.55 if $\geq 0.18$</td>
</tr>
<tr>
<td>3. Q:R amplitude ratio</td>
<td>V_3</td>
<td>Binary</td>
<td>8.46 if $&gt; 0.06$</td>
</tr>
<tr>
<td>4. R amplitude ($\mu$V)</td>
<td>$-aV_R$</td>
<td>Continuous</td>
<td>-0.0093</td>
</tr>
<tr>
<td>5. S amplitude ($\mu$V)</td>
<td>V_5</td>
<td>Binary</td>
<td>5.50 if $&lt; 183$</td>
</tr>
<tr>
<td>6. T amplitude (negative phase) ($\mu$V)</td>
<td>aV_L</td>
<td>Continuous</td>
<td>0.0244</td>
</tr>
<tr>
<td>7. R amplitude</td>
<td>V_2</td>
<td>Ternary</td>
<td>4.76 if $&lt; 302$</td>
</tr>
<tr>
<td>8. Q duration (msec)</td>
<td>aV_L</td>
<td>Ternary</td>
<td>4.83 if $0$</td>
</tr>
<tr>
<td>9. T amplitude (negative phase) ($\mu$V)</td>
<td>III</td>
<td>Binary</td>
<td>6.63 if $&gt; 98$</td>
</tr>
<tr>
<td>10. T amplitude (positive phase) ($\mu$V)</td>
<td>$-aV_R$</td>
<td>Binary</td>
<td>5.72 if $&lt; 146$</td>
</tr>
<tr>
<td>11. T amplitude (positive phase) ($\mu$V)</td>
<td>aV_L</td>
<td>Ternary</td>
<td>3.10 if $\leq 52$</td>
</tr>
<tr>
<td>12. Q duration (msec)</td>
<td>aV_L</td>
<td>Continuous</td>
<td>0.1330</td>
</tr>
<tr>
<td>13. Largest Q duration (msec)</td>
<td>III, $-aV_L$</td>
<td>Binary</td>
<td>4.50 if $\geq 40$</td>
</tr>
<tr>
<td>14. T positive amplitude ($\mu$V)</td>
<td>V_1</td>
<td>Binary</td>
<td>3.91 if $\geq 240$</td>
</tr>
<tr>
<td>15. T amplitude (negative phase) ($\mu$V)</td>
<td>V_2</td>
<td>Binary</td>
<td>5.08 if $\geq 20$</td>
</tr>
</tbody>
</table>

Each discrete (binary or ternary) feature contributes to the total score according to its weight for specified ranges of feature values. The weight coefficient of a continuous feature is multiplied by its measured value and the product is added to (or subtracted from) the score. The features are listed in the order in which they were selected into the linear discriminant function in the sequential step-up procedure.
Discussion

In this study, we show that the classification accuracy of the conventional 12-lead ECG can be substantially improved by improved feature selection and proper optimization of the thresholds of discrete features. The results show that there are ECG features with important diagnostic information for detection of MI that are usually not used in conventional MI criteria. Among these new features are small R and a tall T wave in the inverted aVR lead, an absent Q in aVL, a large T or a negative T in aVL, a negative T in III, a positive T in V1, and a missing S wave in V1. The relative contribution to CIIS by these features from different leads probably depends on the location of the injury, but should be studied further.

The CIIS differs fundamentally from other classification schemes currently used in epidemiologic and clinical applications. Most ECG criteria for myocardial infarction, such as those contained in the Minnesota Code or the IBM ECG analysis program developed by Bonner et al., are based on a sequential, Boolean-type decision tree. Such classification schemes have become popular probably because they are simple, and can be easily learned and adapted to visual coding of ECGs. Optimization of a decision-tree classifier is a difficult statistical problem and unquestionably, the Minnesota Code and other current ECG coding systems are far from optimal.

Like the Minnesota Code, the CIIS scheme uses a set of binary and ternary criteria that can be applied in succession step by step. However, unlike the proper optimization of the thresholds of discrete features. The results show that there are ECG features with important diagnostic information for detection of MI that are usually not used in conventional MI criteria. Among these new features are small R and a tall T wave in the inverted aVR lead, an absent Q in aVL, a large T or a negative T in aVL, a negative T in III, a positive T in V1, and a missing S wave in V1. The relative contribution to CIIS by these features from different leads probably depends on the location of the injury, but should be studied further.

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Like the Minnesota Code, the CIIS scheme uses a set of binary and ternary criteria that can be applied in succession step by step. However, unlike the
Minnesota Code, the CIIS scheme is not based on a “yes/no” decision at any given node of the decision tree. Instead the outcome of each decision contributes in a weighted proportion to the final score. This decision-theoretic approach improves classification stability. In test runs reported earlier,\(^3\) incorrect representation of one feature resulted in a change in infarct/noninfarct classification on the average in slightly over 10% of the records. In contrast, one error at any node of a decision-tree classifier can easily lead to a complete misclassification.\(^2\)

Unlike the commonly used decision-tree ECG classifiers, which tend to favor unconditional yes/no and infarct/noninfarct outcomes from classification, the CIIS expresses the likelihood of an infarction on a continuous scale. The continuous distributions of CIIS in each study group can improve the statistical power of detecting differential trends in study populations, for instance, between treatment groups in clinical heart disease intervention and prevention trials. To simplify the use of CIIS, it may be helpful in many practical applications to use the discrete features of CIIS (table 3), which also apply for changes of CIIS in case of serial comparison of annual ECGs.

The CIIS belongs to a family of statistical classifiers sometimes characterized as decision-theoretic. The best known decision-theoretic ECG classification program is the Bayesian-type multivariate program developed by Pipberger et al.\(^14\) for Frank-lead ECG. The decision-theoretic classifiers, sometimes called second-generation ECG programs,\(^18\) have not gained widespread acceptance for a variety of reasons, even though theoretically they should improve the accuracy of classification.\(^18\) Unquestionably, the unfamiliarity of potential users with the Frank-lead system and the vectorcardiographic features used has delayed the acceptance of the second-generation ECG programs. Conceptual difficulties encountered by the uninitiated with the probabilistic Bayesian statistical approach have confounded these problems, particularly regarding proper use of prior probabilities, which is mandatory for optimal classification. The CIIS coding system combines the simplicity of the first-generation ECG classification schemes with the statistical power and stability achieved by the second-generation ECG programs. These advantages should facilitate the use and acceptance of CIIS.

The grouping of ECG leads in the CIIS scheme differs substantially from that in the Minnesota Code. The Minnesota Code has three groups of leads: I, aVL, and V\(_6\); II, III and aVF; and V\(_1\) to V\(_6\). We found that the statistical distributions of durations and amplitudes of many ECG features could be considerably narrowed both in the infarct and noninfarct groups by avoiding combinations of leads that differ widely in the orientation and strength of their lead vectors.

The diagnostic accuracy of a classification system depends on the prevalence of infarcts in the population.\(^17\) Two groups of investigators can reach markedly different conclusions on diagnostic accuracy of a classifier even when both groups use identical criteria to select their test groups. This apparent paradox can occur if there are large prevalence differences in the populations from which the test groups are chosen.\(^18\)

For a Bayesian-type second-generation computer-ECG program, the classification accuracy can be maximized by matching the prior probabilities to the expected prevalence of different conditions in the specific population in which the classifier is used. With the CIIS scheme, an equivalent adjustment is achieved by the use of graded severity levels. In clinical populations with a high prevalence of infarcts, a CIIS level of 10 acceptably classifies a given record as an infarct, whereas in populations with a very low prevalence of infarcts, a CIIS level of 20 or higher score would be more appropriate.

An 85% sensitivity for detecting myocardial infarctions in the test group with 95% specificity (i.e., 5% false positives) and a 71% sensitivity with 99% specificity is an encouraging sign of the practicality of the CIIS.

We included the hypertensive patients with the normal subjects in the pooled noninfarct group because hypertensive subjects are an important subgroup in many clinical trials and epidemiologic studies. Hypertensive subjects frequently have ECG changes that may considerably complicate the design of a classifier with high specificity and adequate sensitivity. The performance of a classifier designed only to separate normal subjects with patients with infarcts is unrealistic and misleading in a practical application.

It is not possible from the present study to determine how well the CIIS can identify the anatomic location of the infarct, because no ECG-independent data on the location were available from the acute phase. The division into three groups according to the location was made arbitrarily from the postevent rather than from the acute phase record. An investigation is needed to examine how the different CIIS components from different leads or lead groups can best be used to identify the location of the infarct.

Changing electrocardiographic recording technology can significantly alter the validity of any ECG criteria for myocardial infarction; for instance, by altering the width of the baseline of paper tracings used for visual ECG coding.\(^18\) This fact must be considered when using the CIIS scheme, even though it should prove relatively resistant to minor aberrations in the fidelity or quality of the records.

Appendix 1 presents detailed practical considerations regarding the definitions, measurement and coding rules for CIIS. Perhaps the most significant departure from the Minnesota Code is that the amplitude threshold for “codable” waves is 25 \(\mu\)V instead of 100 \(\mu\)V. The measurement rules for CIIS call for a systematic use of the majority rule when beat-to-beat deviations are observed in the quantities measured. In computer-based coding, a representative complex derived on the basis of selective averaging or a median value of the values measured from normally conducted complexes offers an effective alternative.

All amplitude measurements for CIIS are per-
formed with respect to the PR baseline. The scoring criteria may not be valid if TP baseline is used. In our experience, there are many ambiguities in the Minnesota Code definitions for ST- and T-wave measurements. To avoid these logistic problems in ECG coding, the CIIS defines T-wave amplitudes, for its positive and negative phase, as the absolute values of the largest positive and negative deflections in a window extending from 80 msec after the end of QRS to the end of T. This definition is easy to implement for visual and computer coding, and reflects the contribution of ST to the CIIS in the acute phase of infarction when the distinction between ST and T becomes obscure.

The CIIS coding scheme is being evaluated in several large clinical trials to determine its prognostic value and its value in detecting differential trends in treatment groups as a quantitative measure of the effectiveness of intervention. Initial test runs with the visual CIIS coding scheme indicate that with relatively little practice, a technician can code more than 20 ECGs an hour by using a printed coding sheet containing a checklist of CIIS items.

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Appendix

Measurement and Coding Guidelines for the Cardiac Infarction Injury Score

General Considerations

The writing characteristics of the direct-writing electrocardiograph can significantly influence electrocardiographic measurements.8 Of particular concern is the baseline width with pressure-sustained ink recorders, which can produce a bias in ECG wave durations. The baseline width produced by a round recording stylus of uniform thickness should be less than 0.2 mm if a paper speed of 50 m/sec is used.9 The electrocardiograph should meet the minimal specifications established by the ECG committee of the American Heart Association.10

The measurement and coding rules specified here differ from commonly used conventions such as those established for the Minnesota Code.4 41 For CIIS, “codable” waves are defined using a higher resolution than in the past. In general, a wave with an amplitude ≤25 μV (0.025 mV) or more is recognized as a codable wave. Microprocessors and computers are increasingly used for ECG acquisition and preprocessing, and it would be feasible to provide, even for visual coding, a display format with much better resolution than 25 μV. However, because the standardization of the voltage scale at 10 mm for 1 mV is still common practice, the 25-μV threshold corresponding to 1/4 mm on the conventional ECG scale seems a practical compromise at this time.

Another difference is that the CIIS scheme follows the majority rule with exceptions. Complexes with artifacts or excessive noise interfering with measurement are omitted from consideration regarding the majority rule. If computer preprocessing or totally automated processing facilities are available, suitable alternative for the majority rule is the use of the median value of measurements done on a beat-by-beat basis, or a representative averaged
complex derived after clustering of all complexes found for a given lead or lead group, followed by alignment and selective averaging of complexes.\footnote{22}

The CIIS coding scheme is not hierarchical like the Minnesota Code. This implies that each of the 15 components of the CIIS is evaluated separately and independently. All ECG interval measurements and identification of time reference points, such as the beginning and the end of the QRS complex, should be performed from at least three simultaneously recorded, time-coherent ECGs.

**Definition of Codable Waves**

The reference potential or the baseline for all amplitude measurements without exception is the PR segment immediately preceding the earliest part of the QRS complex.

*First wave* within the QRS complex is the earliest deflection, positive or negative, 25 \( \mu \text{V} \) or more in amplitude regardless of its duration.

The first wave is an initial \( R \) wave if it is positive, and a \( Q \) wave if it is negative. (For CIIS coding, no distinction is made between \( Q \) and \( QS \) waves).

*Second wave* within QRS is a deflection exceeding 25 \( \mu \text{V} \) in amplitude with a sign opposite to that of the first wave within QRS. Subsequent waves within QRS, positive and negative, with alternating signs, are defined similarly.

*Amplitude* is the amplitude of the highest positive wave within QRS.

*ST amplitude* is the absolute value of the most negative wave within QRS after an \( R \) wave.

*QR ratio* is measured as the ratio of the absolute amplitudes of \( Q \) and \( R \) waves. A pattern with a \( QS \) wave is considered to have an infinite QR ratio.

*J amplitude* is the signed value of the ST segment at the end of the QRS complex.

*ST amplitude* is the signed value of the ST segment 80 msec past the end of the QRS complex.

*Positive T amplitude* is the highest amplitude of the positive portion of the ST-T complex measured in the window extending from 80 msec past the J point to the end of the T wave.

*Negative T amplitude* is the absolute value of the most negative part of the ST-T complex measured in the window 80 msec past the J point to the end of the T wave.

The sample tracing in figure 1 illustrates various steps involved in CIIS following the sequence given in table 3.

(1) *Q wave duration in lead aV \(_L\)*. Measure Q wave duration to nearest 10 msec. In this record, the \( Q \) duration is 20 msec. Check 3 points on the coding form of table 3. The absence of the \( Q \) wave in a\( V \) is scored 5 points (i.e., no initial negative deflection \( \frac{1}{4} \) mm or more in amplitude.

(2) *T-wave amplitude in aV \(_L\)*. Three points are added to the score if no positive portion of the T wave is 0.5 mm or more or if any portion of the T wave is 3 mm or more. The time window for measurement of T amplitude extends from 80 msec past the end of QRS (4 mm at a paper speed of 50 mm/second) to the end of the T wave. In the sample tracing (fig. 1), the T wave is flat, i.e., less than 0.5 mm. The score is 3 points. (If the T in a\( V \) were negative, 2 more points would be added to the score for each millimeter of negative amplitude.)

(3) *R amplitude in the inverted aV \(_R\) lead*. In the conventional a\( V \) lead, this item can be measured as the amplitude of the most negative deflection within QRS complex (a \( Q \), \( S \) or \( QS \) wave). One point is subtracted for each millimeter of R-wave amplitude in the inverted a\( V \) lead (\(-aV\)\(_R\)) in our sample tracing the R wave is 10 mm, and 10 points are subtracted from the score.

(4) *T amplitude (positive phase) in \(-aV\)\(_R\)*. A flat or small T wave in \(-aV\)\(_R\) leads to the score and a tall T wave subtracts from the score. In our case, the most positive deflection in the T window is clearly less than 0.5 mm, and six points are added. If the conventional (noninverted) a\( V \) lead is used, the absolute amplitude of the negative portion of the T wave is measured under this item.

(5) *Q:S amplitude ratio in leads II and aV \(_R\)*. A \( Q \) wave 5% or more of the R wave in \( \text{either} \) lead adds 12 points to the score. In our sample record, the R wave is clearly less than 20 times the Q-wave amplitude. Score 12 points.

(6) *Q-wave duration in leads III and \(-aV\)\(_L\)*. A 40-msec or larger Q wave in either lead scores 5 points. The initial \( R \) wave (\( \frac{1}{4} \) mm or more) in the lead a\( V \)\(_L\) identical to the inverted a\( V \)\(_R\) lead is scored. There is no Q wave in lead III and there is no initial R wave in a\( V \)\(_L\), so no points are scored.

(7) *T-wave amplitude in lead III*. If any portion of the T-wave measurement window is more negative than 1 mm, 5 points are scored. In figure 1, no points can be attributed to this item.

(8) *T amplitude in lead V\(_a\)*. A positive portion of the T wave (at any point 80 msec past the end of QRS) exceeding 2 mm adds 5 points to the score.

(9) *R amplitude in lead V\(_a\)*. A small or absent R wave (<3 mm) or a tall R wave (\( \geq 14 \) mm) contributes 5 points. In figure 1 there is a QS in lead V\(_a\), which adds 5 points.

(10) *T amplitude in lead V\(_a\)*. Any negative T-wave segment contributes 5 points. In figure 1 there is a biphasic (positive/negative) T wave in lead V\(_a\). However, the negative portion is less than \( \frac{1}{4} \) mm with respect to the PR baseline, so no points are scored.

(11) *Q:R amplitude ratio in lead V\(_a\)*. A QS wave, or a Q wave 1/20 of the R wave, scores 9 points, as in figure 1.

(12) *S amplitude in lead V\(_a\)*. A small (<2 mm) or absent S wave in lead V\(_a\) scores 5 points. The S amplitude in lead V\(_a\) is clearly less than 2 mm in figure 1 and scores 5 points.

The total score from all 12 components is 38 points (48 positive and 10 negative points), and falls into CIIS severity level A.
Cardiac infarction injury score: an electrocardiographic coding scheme for ischemic heart disease.
P M Rautaharju, J W Warren, U Jain, H K Wolf and C L Nielsen

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