Use of a Novel Rule-based Expert System in the Detection of Changes in the ST Segment and the T Wave in Long Duration ECGs

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Abstract: The development of a new fast and robust computerised system is examined in detecting electrocardiogram (ECG) changes in long duration ECG recordings. The system distinguishes these changes between ST-segment deviation and T-wave alterations and can support the produced diagnosis by providing explanations for the decisions made. The European Society of Cardiology ST-T Database was used for evaluating the performance of the system. Sensitivity and positive predictive accuracy were the performance measures used and the proposed system scored 92.02% and 93.77%, respectively, in detecting ST-segment episodes and 91.09% and 80.09% in detecting T-wave episodes. By using the chi-square test we also compared the performance of the system between ECG recordings with minimal and substantial amount of noise. The sensitivity of the proposed system is higher than of other algorithms reported in the literature and the positive predictive accuracy is comparable to, or better than, most of them.
Key words: Computerized detection of ECG changes, ST-segment episodes, T-wave episodes, medical expert system.

Diagnosis of ischemic episodes based on 24-hour ambulatory electrocardiograms (ECGs) or ECG monitoring in the coronary care units is useful in the management of coronary artery disease (1–3). Several techniques that automate the detection of ischemic episodes in long duration ECGs have been developed during the last decade. These techniques, depending on the computational paradigm used, can be categorized to rule-based expert systems, fuzzy expert systems, artificial neural networks, statistical methods, systems based on wavelets theory, and principle component analysis (4–13). However, the currently used techniques have either rather low performance in detecting ischemic episodes (fuzzy systems) or they are unable to specify the nature of the ECG changes (artificial neural networks).

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Recently published literature suggests that the prognosis of unstable angina patients who on admission have ECGs with ST-segment changes is worse than of those with T-wave changes only (14). This finding is also possibly important, in terms of prognosis, for those patients with coronary artery disease being monitored on the coronary care unit or investigated with 24 hours ambulatory ECG.

We have developed a new rule-based expert system for the detection of ECG changes suggestive of ischemia (ST-segment deviation and/or T-wave changes) in long duration ECG recordings. This system is able to distinguish between episodes of ST-segment deviation and T-wave changes. In the present study, we examined the performance of this system in long duration ECG recordings.

Materials and Methods

Description of the Rule-based Expert System

Expert systems are intelligent computer applications that provide decision support through acquisition and processing of human experts knowledge. A rule-based expert system is an expert system based on sets of rules that are used to make decisions. To design an expert system a knowledge engineering process is needed, in which the rules used by human experts are accumulated and translated into an appropriate for computer processing form. The under evaluation system is implemented on a 450 MHz processor and has 4 stages: a) ECG signal processing and analysis, b) Beat classification, c) Window characterization, and d) Identification of episodes with ECG changes (ST-segment deviation and T-waves changes) (Fig. 1). In addition, it is completely automated and does not require any manual interaction during its execution. Initially, the ECG recording is preprocessed in order for the noise to be removed and all ECG features (isoelectric line, QRS complex, ST segment and T wave), which will be subsequently used, to be extracted. For this reason, we developed a module that eliminates the baseline wandering (BW), inactivates the power line interference (A/C), and handles the electromyographic contamination (EMG), while the original signal remains unaffected (15). Specifically, BW is a slow type of noise that can be approximated for short intervals by a low order polynomial (16). Considering this, for each cardiac beat the first order polynomial that best fits it was estimated. BW was eliminated by the subtraction of

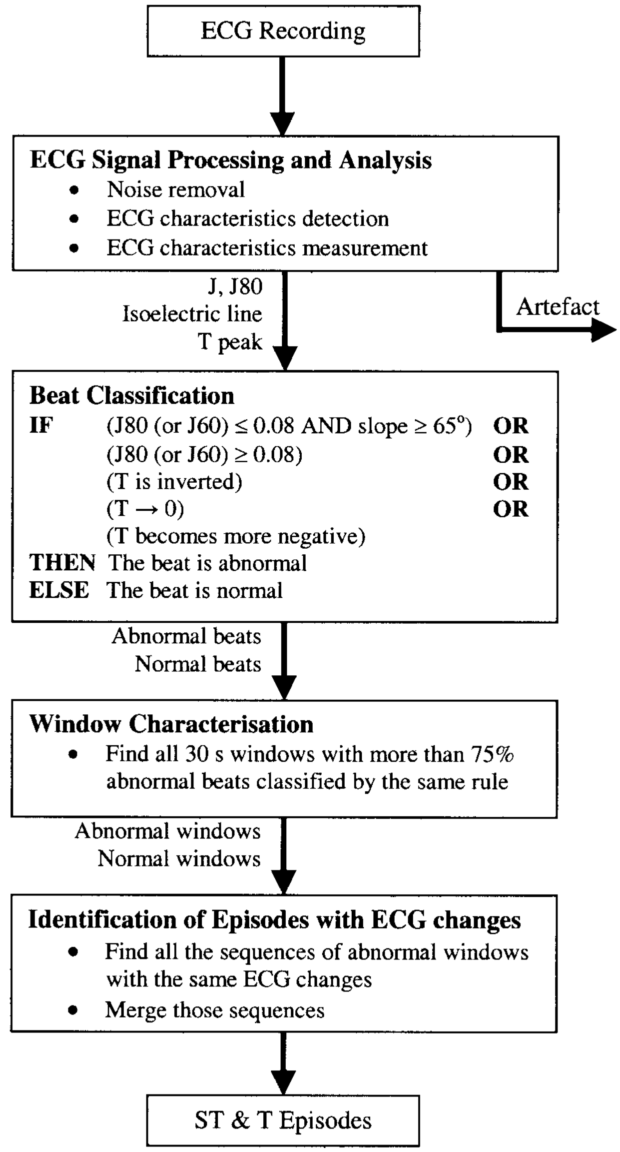

Fig. 1. The 4-stage algorithm of the proposed rule-based expert system.

this polynomial from the recorded beat. To address the problems of A/C and EMG a 20 ms averaging filter was applied before and after the QRS complex. It should be noted that the averaging procedure was used only for defining the isoelectric line and detecting the J point (start of the ST segment). This means that in the second stage of the system, where the ST segment and the T wave are measured and evaluated, the previous signal is used, which is free from BW but not from A/C and EMG. The filtering of these 2 types of noise would introduce distortions in the signal, affecting the measurements in the second stage.

For faster QRS complex detection and more accurate isoelectric line and ST-segment definition we used previously described algorithms after been modified (17,18). More precisely, to make the QRS detector faster, the 300 ms that follow each detected QRS were discarded. Apparently, the detector will fail in cases with heart rate ≥200 beats min^{-1}, but these cases are beyond the study of ischemia. Also, in the edge-detection algorithm that was used to define the isoelectric line and the J point, a stricter signal slope criterion was applied ($C_s \leq 2.5\ \mu V\ ms^{-1}$ instead of $C_s \leq 5\ \mu V\ ms^{-1}$) and better results were obtained. As for the T wave, the peak was defined as the point that lies after the J80 point (80 ms after the J point) and has the maximum difference in amplitude from that of J80. T-wave peaks of the first 30 s of each recording were averaged and used as the reference to detect changes in T-wave amplitude.

After all the ECG characteristics (relevant to the detection of changes in the ST segment or the T wave) were recognized by the system, each beat was classified as normal, abnormal or artefact. The beat classification was based on: a) Negative ST deviation (≥0.8 mm below the isoelectric line and with a slope ≥65° from the vertical line, or in other words with signal slope at the ST segment ≤ 1.87 mV ms^{-1}), b) Positive ST deviation (≥0.8 mm above the isoelectric line), c) T wave inversion, d) T wave flattening (≥50% amplitude decrease), and e) Amplitude increase of a negative T wave (≥50% and ≥0.2 mV). The ST deviation was measured at the J80 (heart rate < 120 beats min^{-1}) or the J60 point (heart rate ≥ 120 beats min^{-1}). The ST slope was defined as the slope of the line connecting the J and J80 (or J60) points. The J point amplitude used in the above measurements was the averaged amplitude in the interval [J − 4 ms, J + 4 ms]. Similarly, for the J80 (or J60) point, the interval [J80 − 4 ms, J80 + 4 ms] (or [J60 − 4 ms, J60 + 4 ms]) was applied. The peak of the T wave was used for the T wave measurements. The rules described above are shown graphically in Figure 2.

During the window characterization stage, all the cardiac beats were examined in groups (windows). The first window was the sequence of the first cardiac beats of approximately 30 s in duration. The next window was created by the subtraction of the first beat and addition in the end of the number of beats needed in order for another interval of 30 s to be created. This was repeated to the end of the recording. The beats of each window were examined and the window was classified as normal or abnormal. A window was characterized as abnormal when it contained more than 75% of abnormal beats with the same ECG pattern changes (ST-segment deviation or T-wave changes).

In the fourth stage, consecutive windows classified as abnormal due to similar ECG changes (ST-segment deviation or T-wave changes) were concatenated to define the starting and ending points of an ST (ST deviation) or T (T-wave changes) episode. In cases in which normal intervals of duration less than 30 s appeared between 2 abnormal windows, the process of merging was continued not allowing thus the fragmentation of the ST or T episodes. After the merging procedure was applied in each of the recorded leads separately, the findings of each lead were combined to identify the duration of each ST or T episode.

Study Population

The European Society of Cardiology (ESC) ST-T database was utilized. This was developed especially for the evaluation of algorithms designed to analyse ST and T wave changes (19). It consists of 90 continuous two-channel recordings, 2 hours each, taken from 79 different ambulatory ECGs. The ECGs were provided by 13 research groups of 8 different countries. Each record of the database was submitted to 2 participating groups of experts for beat-by-beat annotation and then the annotated records returned to the coordinating group for the final annotation. The database records refer to each lead separately outlining the starting and ending points of the episodes and defining the type of ECG changes for every lead (eg, ST-segment deviation of ≥0.1 mV and T-wave amplitude change of ≥0.2mV). We applied a merging procedure for the margins of the episodes to refer to the findings of both leads in order to obtain an overall annotation (lead independent) of the ischemic episodes (15). Also, for the purposes of the present study, the T episodes in which the polarity of the positive T waves was increased and were annotated in the database as T episodes were excluded as they refer to myocardial infarction rather than myocardial ischemia (20,21).

The original analogue signals were recorded by using a variety of two-channel ambulatory ECG recorders: ICR 7200 (37 records), Del Mar Avionics 445B (14 records), Oxford Medilog 4-24 (12 records), Oxford Medilog MR-14 (2 records), Oxford Medilog MR-20 (14 records), Oxford Medilog MR-35 (2 records), Oxford Medilog MR-40 (2 records), Ela Medical 2448 (3 records), Reynolds

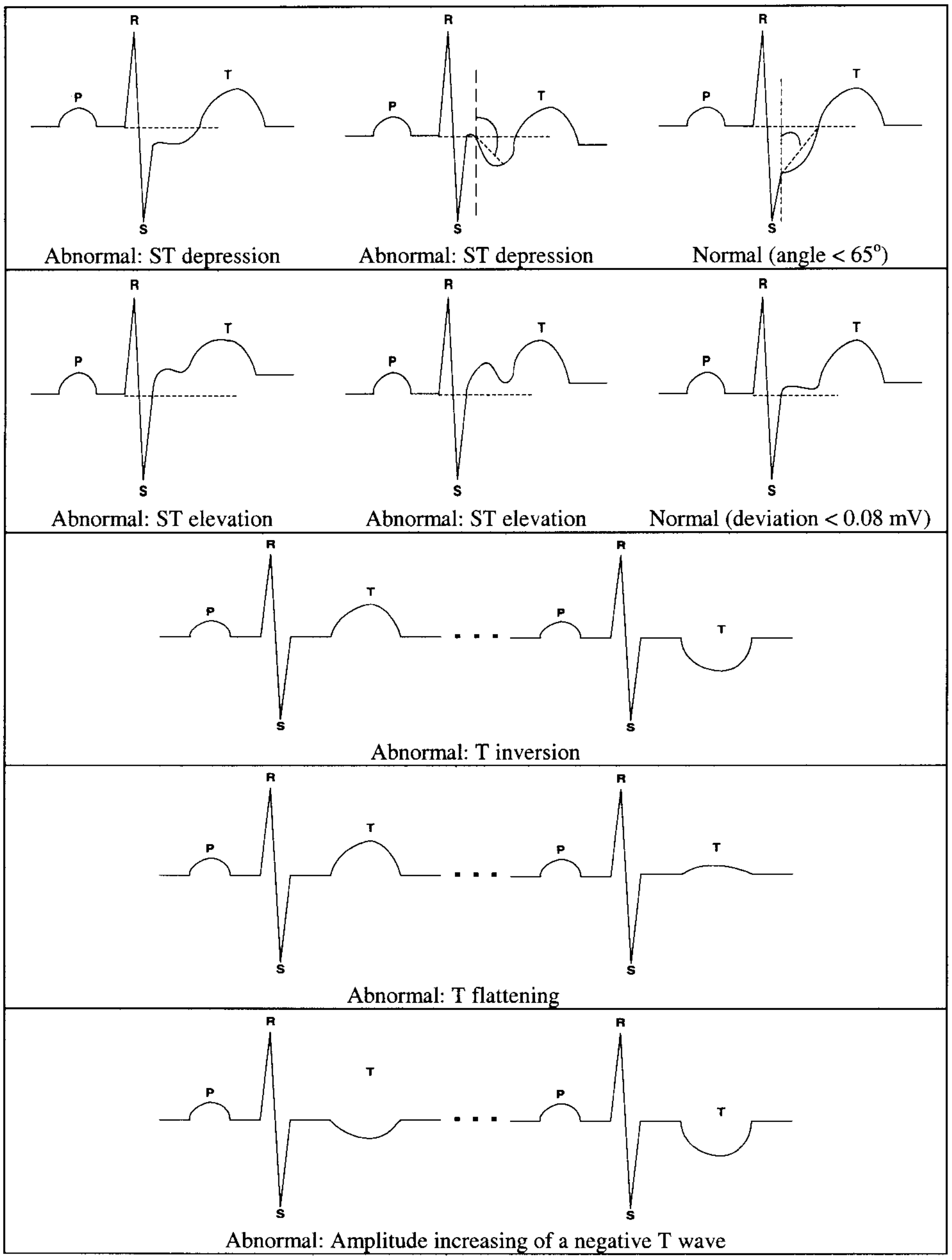

Fig. 2. Five cases of ECG signal alterations suggesting ischemia that correspond to each one of the 5 rules used by the proposed rule-based expert system.

Tracker (3 records) and Applied Cardiac Systems (1 record).

Using the noise information provided by the ESC ST-T database, we separated the 90 ECG recordings in 2 groups: group A (ECGs with minimal amount of noise: number of noisy beats $<$10% of the total number of beats) and group B (ECGs with substantial amount of noise: number of noisy beats $\geq$10% of the total). Group A consists of 64 ECGs and group B of 26 records (e0107, e0115, e0118, e0119, e0121, e0133, e0139, e0148, e0155, e0159, e0170, e0205, e0213, e0406, e0415, e0515, e0601, e0607, e0611, e0612, e0613, e0614, e0801, e0808, e0817 and e0818).

Performance Assessment of the Rule-based Expert System

The performance of the new rule-based expert system in detecting episodes of ST-segment deviation and T-wave changes was assessed in the total number of ECG recordings of the ESC ST-T database and in the groups A and B. To assess the performance of the under evaluation system we used the sensitivity and the positive predictive accuracy. Sensitivity was defined as the ratio of the number of episodes correctly detected as abnormal to the total number of the abnormal episodes, while positive predictive accuracy as the ratio of the number of

Table 1. Performance of the New Rule-based Expert System in the 3 Studied Groups

ECG change		Sensitivity		Positive Predictive Accuracy	
		Episodes	%	Episodes	%
	All ECGs	542/589	92.02	542/578	93.77
ST segment	Group A	377/409	92.18	377/393	95.93
	Group B	165/180	91.67	165/185	89.19
	All ECGs	358/393	91.09	358/447	80.09
T wave	Group A	242/266	90.98	242/303	79.87
	Group B	116/127	91.34	116/144	80.56

correctly detected abnormal episodes to the total number of the detected episodes. Positive predictive accuracy was used instead of specificity, which is not applicable, because the number of nonevents (normal episodes) is undefined when episode detection is under study (22). The time needed for the processing of an ECG recording was reported in each case. This time corresponds to the execution time of the four stages of the system for both leads of the recording.

Statistical Analysis

The new system was validated, regarding its sensitivity and positive predictive accuracy, in detecting episodes of ST-segment deviation and T-wave changes in the total number of ECG recordings and in the ECGs with minimal and substantial amount of noise. In every case aggregate gross statistics was used. To compare the performance of the under evaluation system in ECGs with minimal and substantial noise the chi-square test was used. The processing time for ECG recordings was expressed as mean value ± one standard deviation.

Results

The sensitivity and positive predictive accuracy of the new system in the 3 groups of ECG recordings (total number of ECG recordings, groups A and B) are shown in Table 1. In the Appendix, the performance of the system in each recording is shown. Figure 3 depicts a graphical evaluation of the system's performance when the presence of noise is taken into account.

Total Number of ECG Recordings

The ESC database consists of 90 ECG recordings with 589 ST and 393 T episodes. Our system detected 578 ST and 447 T episodes and correctly identified 542 and 358, respectively. The sensitivity and positive predictive accuracy of the system for the ST episodes were 92.02% and 93.77%, respectively, and for the T-wave episodes 91.09% and 80.09%. The time needed for the processing of each ECG recording was 439s ± 93s.

ECG Recordings With Minimal Noise (Group A)

The ESC database contains 64 minimal noise ECG recordings with 409 ST and 266 T episodes. Our system detected 393 ST and 303 T episodes and correctly identified 377 and 242, respectively. The sensitivity and positive predictive accuracy of our system for the ST episodes was 92.18% and 95.93%, respectively, and for the T episodes 90.98% and 79.87%. The time needed for the processing of each ECG recording was 433s ± 94s.

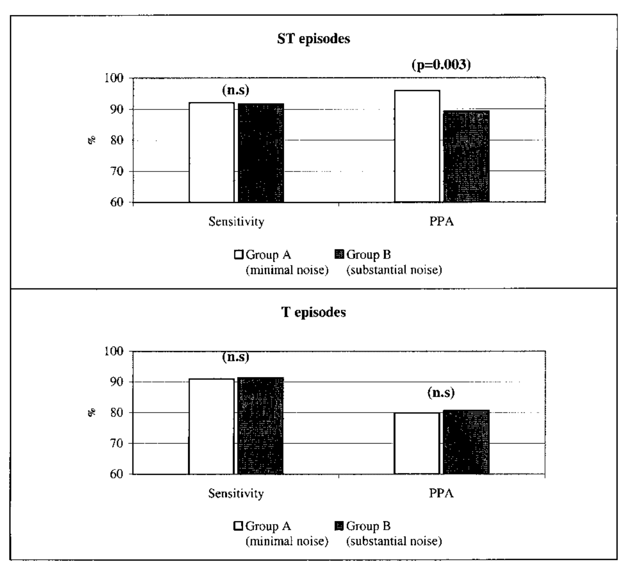

Fig. 3. Graphical representation of the performance of the system (sensitivity and positive predictive accuracy: PPA) in detecting ST-segment and T-wave episodes in long duration ECGs with and without substantial noise.

ECG Recordings With Substantial Noise (Group B)

The 26 ECG recordings in the ESC database with substantial noise have 180 ST and 127 T episodes. Our system detected 185 ST and 144 T episodes. The correctly identified ST and T episodes were 165 and 116, respectively. The sensitivity and positive predictive accuracy of our system for the ST episodes was 91.67% and 89.19%, respectively, and for the T episodes 91.34% and 80.56%. The time needed for the processing of each ECG recording was 455 s ± 91 s.

The sensitivity of the system in detecting ECG episodes of ST deviation was not statistically different in ECGs with and without noise, although its positive predictive accuracy was superior in EGSs without noise ($P = .003$). The new system was able to detect ECG episodes of T-wave changes equally well in ECGs with and without noise (sensitivity and positive predictive accuracy non significantly different).

Discussion

Various algorithms based on sets of rules, fuzzy logic, artificial neural networks, statistics, wavelet theory, principle component analysis, and other signal processing techniques have been proposed for the automated detection of ischemia in long duration ECGs (4–13). Of these algorithms, neural networks perform better than the other systems. Their main drawback, according to the way they have been designed until now, is that they cannot discriminate ST segment from T wave changes as the reason for the diagnosis. Systems based on sets of rules or fuzzy logic, on the other hand, provide information regarding the type of the detected ECG changes but do not have the high diagnostic performance of the artificial neural networks.

The techniques mentioned above have been tested either on the data of the ESC ST-T database (4–8) or on various independent datasets (9–13). In cases in which the ESC ST-T database was used the sensitivity and positive predictive accuracy ranged from 71% to 85.2% and 66% to 90%, respectively. These techniques used only partially the ESC ST-T database when tested. In particular they either used certain ECG recordings, (4–6) or been tested on detecting ischemic beats with ST-segment changes (5) or ST-segment episodes (6–8). The techniques tested on independent datasets had sensitivity and specificity, ranging from 92% to 97.2% and 69% to 96.2%, respectively (9–12). Most of them tested on their ability to diagnose "ischemic patients" rather than detect ischemic episodes and subsequently their performance was judged by their specificity instead of positive predictive accuracy (9–11).

The currently under evaluation rule-based expert system was tested on all the ECG recordings of the ESC ST-T database. Its sensitivity and positive predictive accuracy in detecting ST segment episodes was 92.02% and 93.77%, respectively, while in detecting T-wave episodes 91.09% and 80.09%. This sensitivity is higher than of the previously described algorithms (except those tested on individual datasets) while the positive predictive accuracy is comparable to, or better than, most of them. The current approach is able to clarify the type of each detected episode (different types of ST segment vs. T-wave changes) with high rates of sensitivity and positive predictive accuracy. Furthermore, the performance of the system is not affected by the presence of noise due to its novel noise-handling module, while it exhibits very short decision delay time. The later enables real-time operation providing on line decision support to the medical personnel without any manual interaction.

The innovations of the studied system are the use of certain rules for beat classification, the noise-handling module and the use of a sliding adaptive window. The set of rules for beat classification differentiates T-wave inversion from flattening or increase in the negative amplitude. This was incorporated for the first time in a system for automated diagnosis and possibly increased the positive predictive accuracy of the system. The noise-handling module has the advantage of successfully removing from the recorded ECG signal the 3 basic types of noise (power line interference, electromyographic contamination, and baseline wandering) without altering any of the ECG characteristics. This is important as even slight modifications, especially to the ST segment and the isoelectric line, can lead to inaccurate diagnosis. Also, the sliding adaptive window, applied in the third stage of the algorithm, offers flexibility in the decision making process. Intervals of ECG with ST-segment deviation or T-wave changes containing normal beats were characterized as abnormal whereas stricter algorithms would either miss the episode or produce more episodes of shorter duration.

The performance of the proposed system could be further improved, especially in terms of positive predictive accuracy, through further refinement of the noise-handling procedure. Recordings with very low signal-to-noise ratio often resulted in problematic detection of the J point, the isoelectric line and the T peak. Incorrect T-peak detection at the beginning of the ECG recordings led to false definition of the sign and amplitude of the T wave. This explains the better performance of the system in detecting ST segment than T-wave episodes. Modern ECG recorders and Holter devices include filtering modules and the output ECG signals have higher signal-to-noise ratio than the recordings of the database. Our method would be expected to perform better if the ECG recordings were obtained with contemporary equipment. Also, a limitation of our study is that the designed system was evaluated with only 79 ambulatory patients, those included in the database. This stems from the fact that the ESC ST-T database is the only annotated ECG database that can be used as a reference for myocardial ischemia detectors. Most of the studies in the area use only this database.

In conclusion, this new rule-based expert system rapidly and reliably detects ECG changes suggestive of ischemia in long duration ECGs. Its performance is not affected by the presence of noise and clarifies the type of each detected episode. Whether the advantages of this new system will increase the diagnostic and prognostic accuracy requires further evaluation.

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Appendix

System's Performance for All ECG Recordings of the ESC ST-T Database

Record	ST episodes Se	ST episodes PPA	T episodes Se	T episodes PPA	Record	ST episodes Se	ST episodes PPA	T episodes Se	T episodes PPA
103	6/6	6/6	4/4	4/4	211	2/2	2/2	0/0	0/1
104	12/12	12/12	14/14	14/15	212	0/1	0/0	0/0	0/0
105	6/6	6/6	2/2	2/7	213	2/4	2/2	0/0	0/0
106	11/12	11/11	1/3	1/1	302	8/8	8/8	3/3	3/6
107	4/4	4/7	10/10	10/10	303	1/1	1/1	0/0	0/1
108	22/22	22/22	7/8	7/7	304	5/5	5/5	7/7	7/8
110	3/3	3/3	0/0	0/0	305	1/1	1/1	1/2	1/1
111	11/11	11/11	5/5	5/10	306	2/3	2/2	0/5	0/0
112	6/6	6/6	6/7	6/8	403	22/22	22/22	8/8	8/10
113	4/8	4/4	10/11	10/11	404	9/9	9/9	8/8	8/8
114	13/14	13/13	5/5	5/5	405	8/8	8/8	9/9	9/10
115	5/6	5/5	4/5	4/6	406	1/2	1/1	0/0	0/4
116	1/2	1/3	14/14	14/17	408	2/2	2/2	1/1	1/1
118	8/8	8/10	10/11	10/13	409	2/2	2/2	3/3	3/3
119	9/9	9/9	11/11	11/11	410	1/2	1/1	0/0	0/1
121	3/3	3/6	5/6	5/6	411	4/4	4/4	2/2	2/5
122	1/1	1/5	6/6	6/7	413	4/4	4/9	1/1	1/3
123	3/3	3/3	0/0	0/0	415	7/8	7/7	1/4	1/1
124	4/7	4/4	2/2	2/4	417	6/6	6/6	0/0	0/7
125	1/3	1/1	6/8	6/6	418	11/13	11/11	0/0	0/1
126	1/1	1/1	8/9	8/8	501	4/4	4/4	0/0	0/1
127	1/2	1/1	7/7	7/8	509	1/1	1/1	3/3	3/3
129	10/10	10/10	3/3	3/5	515	3/4	3/4	8/10	8/8
133	0/0	0/0	1/1	1/1	601	0/2	0/2	4/4	4/4
136	7/7	7/7	7/7	7/7	602	11/11	11/11	7/7	7/7
139	3/3	3/3	13/13	13/16	603	9/9	9/9	1/1	1/1
147	7/7	7/7	10/10	10/11	604	1/10	1/1	5/5	5/5
148	11/11	11/11	1/1	1/2	605	2/2	2/2	2/2	2/2
151	15/16	15/15	0/0	0/0	606	5/5	5/5	2/3	2/2
154	1/1	1/1	2/2	2/2	607	14/14	14/14	4/4	4/4
155	9/9	9/9	11/11	11/11	609	3/3	3/3	1/1	1/1
159	2/2	2/2	0/0	0/0	610	4/4	4/4	3/3	3/3
161	15/15	15/15	0/0	0/1	611	0/0	0/0	4/4	4/4
162	8/8	8/8	5/5	5/5	612	4/4	4/7	0/1	0/0
163	4/5	4/4	8/8	8/8	613	9/13	9/10	0/0	0/2
166	16/16	16/21	1/1	1/5	614	19/19	19/19	2/2	2/2
170	3/3	3/7	6/6	6/10	615	7/8	7/7	0/0	0/3
202	8/8	8/8	8/9	8/9	704	8/8	8/8	7/8	7/7
203	2/2	2/2	0/0	0/0	801	0/2	0/0	0/2	0/0
204	0/2	0/0	2/2	2/2	808	14/14	14/14	15/15	15/15
205	5/5	5/6	2/2	2/3	817	17/17	17/17	2/2	2/2
206	5/5	5/5	1/5	1/2	818	13/14	13/13	2/2	2/9
207	4/4	4/4	8/9	8/8	1301	8/8	8/8	4/4	4/5
208	9/9	9/9	0/0	0/0	1302	4/4	4/4	8/9	8/10
210	4/4	4/4	1/1	1/1	1304	1/1	1/1	3/4	3/3

Abbreviations: Se, Sensitivity; PPA, positive predictive accuracy.