

ALGORITHMS FOR IMPROVED DETECTION OF SUPRAVENTRICULAR ARRHYTHMIAS

Shane G. Artis, George B. Moody, and Roger G. Mark

Harvard-MIT Division of Health Sciences and Technology,
Cambridge, Massachusetts, 02139

Abstract

In the present study we developed and tested a post-processing system used for the detection of a subset of supraventricular arrhythmias (SVA): supraventricular tachyarrhythmias (SVTA) and atrial premature beats (APBs).

ARISTOTLE, an existing state-of-the-art arrhythmia detector, is able to detect roughly 75% of the APBs in the MIT-BIH Arrhythmia Database, with a positive predictivity of about 75%.¹ We selected a particularly difficult set of records from a newly-created SVA Database. ARISTOTLE's APC sensitivity for these records is less than 35%, with an APC positive predictivity above 97%. Removing the constraint of real-time analysis imposed on ARISTOTLE's design, we studied alternative SVA detection strategies which incorporate criteria based on examining R-R interval statistics in a wider context ('retrospective analysis') in order to identify isolated APBs more accurately, and other strategies which use explicit 'look-ahead' criteria to find runs of SVTA. Using the 'retrospective analysis' algorithm, we obtained a modest increase in APC sensitivity (to 44%) offset by a decrease in positive predictivity (to 91%). Applying the 'look ahead' algorithm to the output of the 'retrospective analysis' algorithm, the APC sensitivity was 78%, with 91% positive predictivity.

1. Introduction

The extreme difficulty of detecting P-waves in long-term surface-lead ECGs remains an obstacle to comprehensive analysis of supraventricular arrhythmias (SVA), and most if not all arrhythmia detectors rely solely on inferences from R-R intervals and QRS morphology for identification of SVA as well as VA. While these approaches have been shown to work reasonably well for detection of atrial fibrillation and flutter, SVTA detection remains problematic and is less fully studied. Thus far systems such as ARISTOTLE and the Argus/2H arrhythmia detection system² have assigned beat labels based on R-R interval analysis without the aid of post-processing to add contextual information. We have implemented two such post-processors.

Detection of SVTA and APBs is almost entirely a process of R-R interval prediction, with contextual information provided by the surrounding beats. R-R interval prediction algorithms have been based upon moving averages of previous R-R intervals given by

$$RR'_{n+1} = \frac{1}{N} \left(\sum_{i=n-N+1}^n RR_i \right) \quad (1)$$

or based upon a first-order, low-pass digital filter:³

$$RR'_{n+1} = RR'_n + \alpha(RR_n - RR'_n) \quad (2)$$

ARISTOTLE currently uses the latter algorithm with the α parameter set to a value of 0.625. A beat is usually considered premature if its R-R interval is less than 85% of the estimated interval, although in the context of highly variable intervals the criterion for prematurity is made more stringent.

The current algorithm used by ARISTOTLE is effective in detecting isolated APBs throughout slow variations in heart rate, but rapid changes, such as those in SVTA, quickly cause the algorithm to track the increased beat rate rather than the expected normal heart rate. For this reason the ARISTOTLE algorithm is deficient in analyzing SVTA. Much more can be done to detect SVTA and APBs if the context in which each beat is examined is broadened.

2. APB Database

All of the algorithms described in this document were developed and evaluated using a database of pathologically complex records chosen from data made available by Beth Israel Hospital from Holter monitor recordings. Each record consisted of ARISTOTLE-annotated ECG records of 30 minutes in length, and a total of 18 such records were evaluated. The ARISTOTLE annotations formed the basis of the processing of raw ECG data and were then passed to each post-processing algorithm for further annotation and error correction. The 18 records were considered to be reasonable tests of an SVPB detection system because each contained a wide variety of APBs and SVTA embedded in both clean and noisy data. Each record of data was accompanied by a reference file. The reference annotations were created by passing the original data through a Marquette scanner

and having an expert technician edit the results. Additional review and corrections were performed off-line by an independent reviewer. Table 1 summarizes the contents of the database.

Each algorithm described here was tested in an iterative loop. ARISTOTLE was applied to each record in the evaluation database described above and the results were compared to the reference files. Then each developed algorithm was applied to the output annotations from ARISTOTLE and the results were again compared to the reference files. Finally ARISTOTLE's results and the algorithms' results were compared to each other.

2. Pattern Matching

Supraventricular premature beats follow a characteristic R-R interval pattern which may be exploited by a search algorithm. In general, an isolated SVPB, surrounded by normal beats, will have the same morphology as the beats around it. The R-R intervals, however, will distinctly display the beat's prematurity. This characteristic pattern is shown in figure 1.

The algorithm derived from analysis of this pattern was quite simple and may be generalized to include SVPBs in various other combinations of surrounding beats. First, a template was defined into which a set of three R-R intervals had to fit. The second R-R interval had to be less than some percentage of the first, and less than the same percentage of the third R-R interval. An optimum percentage was arrived at empirically.

The algorithm was initialized with the first four beats of the input record, thus providing the first three R-R intervals of the system. Then the pattern was applied sequentially to each beat in the file and beat labels were reassigned on the fly if they fit the pattern. The best prematurity percentage was discovered to be $90 \pm 0.5\%$.

3. SVTA Detection

SVTA requires special treatment by detection algorithms, both because it is crucial that it be detected, for it has clinical significance, and because it is crucial that long periods of normal beats not get mislabelled as premature by faulty algorithms. In addition, SVTA should not be mislabelled as ventricular tachycardia and SVTA mislabelled as normal sinus rhythm should not interfere with the detection of other arrhythmias. Because of these constraints, SVTA detection algorithms must be very consistent and also be implemented conservatively so that false positives (normal beats, incorrectly labelled) do not occur.

SVTA generally follows the same pattern as individual SVPBs except that instead of a single short R-R interval, there are many. In our database no run exceeded 105 beats in length, although SVTA can last much longer. The greatest difficulty in detecting SVTA is that it may appear quite similar to a normal increase in heart rate due to exercise or exertion. The onset and conclusion of SVTA may be distinguished from normal heart rate changes by its very rapid acceleration and deceleration. Figure 2 shows two examples of SVTA in actual data. The first graph depicts a short run, while the second graph shows a somewhat more complex pattern of SVPBs in a run.

Record #	Normal	SVPB	PVC	SVTA & Couplets	Maximum SVTA (bts.)
800	1846	30	6	0	0
801	2174	67	268	5	28
806	2952	40	29	2	6
809	2432	112	0	2	105
816	1550	36	0	2	2
823	2478	382	0	37	3
831	1913	29	0	3	6
833	2465	12	0	1	10
835	2805	15	4	1	11
837	2834	14	24	1	70
840	2341	44	1	1	41
846	1656	20	0	2	14
847	1665	51	44	2	20
850	1830	8	0	2	4
851	2169	32	427	1	5
854	2047	57	532	4	10
855	2035	227	277	5	5
873	1626	15	26	0	0
882	1889	41	5	0	0

Table 1: Summary of the contents of the SVA evaluation database

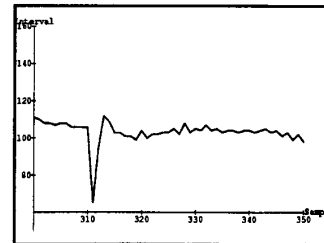


Figure 1: APB as pattern of R-R intervals

The existing ARISTOTLE algorithm relies upon a first order, low-pass digital filter to provide an estimator of prematurity, as described in the introduction. This technique is effective in detecting isolated premature beats, but because it relies on a weighted sum of the previous R-R interval estimator and the current R-R interval, the estimator quickly begins to track the increased heart rate in runs, rather than the true R-R interval value. If premature beats are excluded from the R-R interval estimation procedure, the algorithm's false positive rate for SVPBs becomes excessive during periods of severe sinus arrhythmia or sudden heart rate accelerations. For this reason, a more effective technique is required to detect runs.

The run detector implemented in this study utilizes a concept similar to the low-pass filter which is in use by ARISTOTLE, but with some important differences. First, it acquires a block of 400 beats from its input file. Using ARISTOTLE's annotations (assumed to be accurate with high probability for a large block of beats), an average of all N-N intervals within the block is determined. The goal of determining this average is to provide the algorithm with a reasonable estimate of the N-N interval below which a dynamically determined estimator should not significantly fall.

Once the average N-N interval for the current block of beats has been determined, the run detector steps sequentially through each beat in the current block. As it steps, it maintains and updates an estimator of the expected N-N interval. This es-

timator is nothing more than the most recent N-N interval. If this estimator is ever less than 90% of the average N-N interval it is assumed to be incorrect and is set equal to 90% of the average N-N interval.

As the algorithm steps through the input block of beats, maintaining its estimator, it compares each R-R interval to the estimator and to the average N-N interval (determined earlier). If the current R-R interval falls below 85% of each of these, the beat is labelled premature. When this occurs, the algorithm begins looping through subsequent beats, comparing each R-R interval to the average and the estimator without updating the estimator. The algorithm labels each subsequent beat premature until two successive beats are greater than 85% of the estimator and the average. If the end of a block is encountered, the loop exits, saves the last two beats of the current block, appends 398 new beats to the current block and continues. At this time the average N-N interval is updated to reflect the values in the new block but the estimator is not reset. Because the estimator is not reset, SVTA that crosses block boundaries can continue to be properly labelled if the new average N-N interval is comparable to the old. However, SVTA that approaches the block size in length will depress the N-N interval estimator considerably, putting an upper limit upon the duration of SVTA which can be detected. Using this algorithm the SVTA detector steps sequentially through blocks of 400 beats until the input file is exhausted.

This algorithm improves upon the low-pass filter of ARISTOTLE because it greatly extends the number of beats which must be premature before the estimator begins to track the premature beat R-R interval rather than the normal beat R-R interval. This could be extended indefinitely by explicitly searching for the conclusion of SVTA.

4. Results and Discussion

4.1 Pattern Matching:

The pattern matching algorithm was the first algorithm tested which exceeded ARISTOTLE in accuracy. Table 2 displays a table of comparisons between ARISTOTLE, the pattern-matching algorithm and a combination of the SVTA detector and the pattern-matching algorithms applied to each of the database files. Table 3 compares the sensitivity and positive predictivity of the same cases. The improvement upon ARISTOTLE by the pattern-matching algorithm is relatively minor, as is to be expected, because in data with many premature beats the majority of SVPBs are often found in runs, couplets, or embedded in groups of premature ventricular beats. The algorithm's pattern will not fit these beat groupings. The pattern-matcher will succeed somewhat more often than ARISTOTLE, however, because it relies upon a very specific set of rules to declare a beat premature. In particular, the pattern-matcher uses exactly the same criteria to declare an individual beat premature that a human annotator would use, and thus may use a very small percentage of difference between intervals to correctly label each beat. For example, ARISTOTLE declares a beat premature when its

Record #	ARISTOTLE			Pattern Match			SVTA & patterns		
	True	S/N	N/S	True	S/N	N/S	True	S/N	N/S
800	26	7	3	28	9	1	28	9	1
801	15	0	36	16	1	35	18	1	33
806	28	2	12	31	2	9	32	3	8
809	8	0	104	8	0	104	101	0	11
816	27	0	8	29	0	6	29	0	6
823	174	0	199	217	3	156	287	7	87
831	18	0	9	24	0	3	24	0	3
833	5	1	7	5	1	7	12	3	0
835	6	0	7	6	0	7	11	0	2
837	5	0	66	5	0	66	70	0	1
840	8	1	36	8	1	36	44	1	0
846	13	0	7	13	0	7	20	3	0
847	30	1	18	31	3	17	46	3	2
850	4	0	3	4	0	3	6	0	1
851	11	2	17	11	2	17	15	7	13
854	56	0	330	99	12	287	265	27	119
855	27	1	191	95	33	123	153	54	65
873	11	0	4	15	0	0	15	0	0
882	41	0	0	41	0	0	41	0	0
TOTALS:	513	15	1,057	686	65	864	1,218	119	352

Table 2: Comparison of the results of ARISTOTLE, the pattern matching algorithm, and the SVTA detector. True = correctly labelled SVPB. S/N = Normal beat labelled SVPB. N/S = SVPB labelled Normal

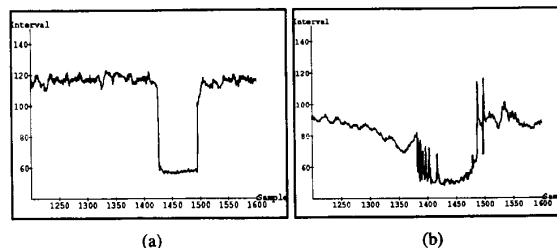


Figure 2: Simple (a) and complex (b) cases of SVTA as patterns of R-R intervals

	ARISTOTLE	Pattern Match	SVTA & Patterns
Sensitivity	0.328	0.443	0.777
+Pred.	0.971	0.913	0.911

Table 3: Lists of sensitivity and positive predictivity for each applied algorithm

R-R interval is 85% of the length of its estimator (15% premature), while the pattern-matcher works successfully when this percentage is 90%. The trade-off for the extra 5% of accuracy is a slight loss in positive predictivity but a still larger gain in sensitivity.

4.2 SVTA detection:

The results of applying the SVTA algorithm to annotated database records are summarized in table 2. In general, the SVTA detector was quite successful at extracting SVTA from noisy data. Successful examples of this include records 809, 833, 837, 840, 846, and 847. Records 854 and 855 also had several successful SVTA detections, but included a high percentage of missed beats, SVTA, and false positives. This was caused by a large number of PVCs in the data. SVTA that was preceded or terminated by PVCs, or other complex combinations of normal beats, PVCs, and premature beats, often proved to be too difficult to successfully recognize. Lowering the various prematurity criteria in the algorithm did not seem feasible because the number of false positives increased significantly in these records as compared to ARISTOTLE.

Experimentation with the SVTA detector indicated that it was fairly insensitive to small variations in its parameters. Unless a change of 3-4% was made in the prematurity percentage, most beat labels remained consistent.

An example of a signal which the SVTA detector analyzes very well, but not perfectly, is shown in figure 2b. This sample of data, taken from database record 809 shows the transition from normal sinus rhythm into an extended period of SVTA. The reference annotations for this record label every beat as premature, but the SVTA detector's annotations periodically mislabel beats as normal. This occurs because P-waves from the atrium are periodically blocked during repolarization of the heart muscle tissue and do not generate QRS complexes. As a result, a pause occurs before the next QRS complex, as seen in the R-R interval graph. This pause evaluates to a normal beat using the run detector because P-wave analysis is never performed. Thus, the SVTA detector cannot attain perfection, and no run detector will approach perfection until P-wave analysis can be performed. Nonetheless, the SVTA detector is highly accurate throughout the remainder of this complex run.

Unfortunately, the run described in the previous example represents one of the longest runs which was available to be tested. We were unable to evaluate the algorithm's performance on runs longer than 105 beats, but it is likely that runs exceeding 200 beats would not be successfully detected by this algorithm. The reason for this conclusion is that the algorithm acquires 400 beats in a block from the input data and evaluates the average N-N interval from that block. Assuming that a run in the block was not acquired by ARISTOTLE, the average N-N interval would be inversely proportional to the number of mislabelled beats. If, for example, S-S intervals in a mislabelled run were 60 samples long, while N-N intervals were 120 samples long, then the average N-N interval for a 200 beat run in a 400 beat block of data would be 90 samples, or only 75% of the correct value. If a beat were labelled SVPB only when its preceding R-R interval was 85% of this average, then any beats following intervals exceeding 76 samples in length would be mislabelled as normal.

The solution to this problem is obviously to increase the block size, thus allowing increasingly lengthy runs to be detected. Unfortunately, a balance must be struck between a block size

which can acquire reasonably long runs, and one which is so long that all effects of normally increased or decreased heart rate (from exertion, for example) are not averaged together. The block size must remain small enough to track the average heart rate through periods of exertion and rest. The value of 400 beats per block is an empirically determined parameter which best fit the data in the SVPB evaluation database. Further study may provide a general solution to this problem, such as explicitly searching for the conclusion of SVTA, which generally appears as a step function in the R-R interval plot (fig. 2a).

In order to test the performance of the SVTA algorithm in exercise data, four 1/2-hour Holter recordings of young and healthy subjects undergoing sudden, strenuous exercise were obtained. Reference annotations were established as usual. The rapid heart rate accelerations accompanying this exercise did not cause false positives using the SVTA detection algorithm.

5. Conclusions

Post-processing modules which evaluate cardiac data with additional context show significant promise as methods of improving the performance of arrhythmia detectors.

References

1. George B. Moody and Roger G. Mark. QRS Morphology Representation and Noise Estimation Using the Karhunen-Loeve Transform. In *Computers in Cardiology*, 1989.
2. K. W. Clark, R. E. Hermes, P. W. McLearn, and C. N. Mead, L. J. Thomas, Jr. The Argus/2H Approach to Supraventricular Arrhythmia Analysis. In *Computers in Cardiology*, pages 165-168, 1981.
3. Roger G. Mark and George B. Moody. *Arrhythmia Analysis, Automated*. Encyclopedia of Medical Devices & Instrumentation, Vol. 1, pages 126-127. John Wiley & Sons, Inc., New York, NY, 1989.