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Automatic Atrial Arrhythmia Detection Based on RR Interval Analysis in Conscious Rats

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Abstract—Telemetry devices for electrocardiographic (ECG) recording in conscious rats make it possible to obtain long-lasting recordings over extended periods of time, which raises the need for an automatic arrhythmia detection procedure. Numerous algorithms of arrhythmia detection have been developed for analyzing human ECG data. These algorithms, however, are not well suited for recordings characterized by nonsustained arrhythmias and variable QRS morphology, hence the need for a new algorithm. In 5 spontaneously hypertensive rats, 24-h ECG recordings were obtained once a month, from 6 to 11 months of age. A common algorithm detected R peaks, and artifacts were discarded either visually or by using an automatic procedure. All atrial and ventricular tachyarrhythmias were visually assessed. Using RR interval time series, automatic identification of tachyarrhythmias was performed by a fuzzy automaton. Parameters of the automaton were optimized using a cross-validation technique. The thirty 24-h recordings yielded a total of 161,615 atrial arrhythmic beats and 5186 ventricular arrhythmic beats. The automatic procedure provided a high sensitivity (0.89) and positive predictive value (0.91). This new algorithm is appropriate for telemetric recordings of ECG in rats, and allows a fully automatic, computationally efficient procedure for arrhythmia detection with a good performance.

Keywords—Atrial tachyarrhythmia, Automated analysis, Fuzzy automaton, RR interval signal.

INTRODUCTION

Radiotelemetric devices are commonly used in rodents to assess long-term effects of various interventions or pharmacological treatments on cardiovascular variables such as arterial blood pressure or heart rate. The radiotelemetry technique makes it possible to obtain repeated measurements over extended periods of time in conscious, fully unrestrained animals maintained in their usual environment. A corollary of this technique is that the investigator has to deal with a huge amount of data. We have recently used this methodology to identify episodes of unprovoked atrial tachyarrhythmia (AT) from 24-h electrocardiographic (ECG) recordings in aging spontaneously hypertensive rats (SHR).[13] In the latter study, ECG data were visually inspected by two well-trained investigators to ascertain the presence of AT episodes, including atrial fibrillation and multifocal atrial tachycardia. We found it necessary to analyze the totality of the 24-h recordings because of the large variability of AT occurrence throughout the day. This extremely time-consuming procedure prompted us to develop an automatic method for characterizing the arrhythmic profile over long periods of time in conscious rats.

Numerous algorithms have been developed to address the issue of automatic cardiac arrhythmia detection in humans. Most of them can be classified in two categories:

- Algorithms that classify each beat, according to its morphology. This approach allows the investigator to detect various arrhythmias, such as ventricular or atrial premature beats, right or left bundle branch block beats, paced beats,[6] congestive heart failure beats,[16] non-conducted P-waves.[3]
- Algorithms that classify ECG sequences (usually a fixed number of beats) as sinus rhythm or atrial fibrillation, by computing several statistical indices of the RR interval time series. Examples of such indices include standard time domain indices (SDNN, RMSSD),[17] Shannon entropy[2] or sparseness of RdR plot.[8]

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Both approaches are not suitable for detecting AT episodes in rats. In contrast with premature ventricular beats, the QRS complexes corresponding to ectopic atrial beats are similar to QRS complexes driven by sinus beats. Moreover, P waves frequently exhibit very low amplitudes and sometimes are not even distinct from isoelectric noise. Therefore, any analysis based solely on wave (QRS complex or P wave) morphology would be unable to identify all ectopic atrial beats. On the other hand, algorithms classifying ECG sequences need a minimal number of RR intervals to accurately compute the statistical indices. Studies report using 64 or 128 beats for an optimal accuracy,[2,8,17] and reducing the length of sequences lowers the performance of the detection. In rats, however, AT episodes are mostly composed of very short sequences (<1 s on average),[13] so that algorithms that classify ECG sequences as normal or arrhythmic would miss a lot of short-lasting episodes.

Thus, a new algorithm was required to detect AT in telemetric recordings of ECG in rats. The proposed algorithm only relies on RR intervals, because, as mentioned above, P waves cannot be safely identified in the whole recording, as opposed to QRS complexes which are the most robust feature that can be extracted from the ECG signal. Nevertheless, because of noise in the ECG signal, an automatic procedure was also needed to remove misclassified QRS complexes.

The algorithm has an automaton structure that classifies each beat as normal or arrhythmic, based on the RR interval time series. This structure is often used to find patterns in series, and as it acts in one pass, it requires a very low computation time.[1] In this study, the automaton was set to detect sequences of reduced RR intervals followed by a longer RR interval, which characterizes arrhythmic beat sequences. Under the strict conditions of the automaton, however, RR interval patterns formed by arrhythmic beats were not always discriminated from normal RR interval sequences. By using a fuzzy automaton, where strict conditions are replaced by probabilities, we aimed at improving arrhythmia detection.

MATERIALS AND METHODS

Data Collection

Details of surgical procedures can be found in Scridon *et al.*[13] Briefly, male SHRs ($n = 5$) were purchased from Elevage Janvier (Le Genest Saint Isle, France). All experiments were performed in compliance with the French Ministry of Agriculture guidelines for animal experimentation, and were approved by the local Animal Ethics Committee. Radiotelemetry ECG transmitters (TA11 CA-F40; Data Sciences International, St. Paul, MN) were implanted under isoflurane anesthesia at least one week before starting recordings. Continuous 24-h ECG recordings were performed once a week at the ages of 26, 30, 34, 38, 42 and 46 weeks, which makes a total of 30 recordings. ECG signals were sampled at 2000 Hz and stored on hard drive. The different procedures are schematized in Fig. 1 and detailed below.

R Waves Detection

All analysis tools were developed using LabVIEW 2010 software (National Instruments, Austin, TX). R waves were automatically detected using an algorithm adapted from Pan and Tompkins.[11] ECG signals were first transformed by a second-order Butterworth low-pass filter (125 Hz) to suppress high frequency noise. This was followed by a numerical differentiation to emphasize QRS complexes, which have sharp slopes, as opposed to P and T waves. The signal was then squared to obtain only positive values and to prepare for peak detection. However, as several peaks could be observed within a single QRS complex, the signal was smoothed by low-pass filtering (25 Hz). Cutoff frequencies were adapted from the original study in humans[11] to the rat ECG characteristics. Local maxima were noted on the filtered signal and validated as QRS complexes if their amplitude was higher than 15% of the median amplitude of the 5 preceding QRS complexes. If no QRS complexes were detected during one second, then the amplitude threshold was reset to the mean of the full signal calculated over that second. Finally, R waves were located on the original, non-filtered ECG as local maxima within a window of 20 ms before a QRS complex in the filtered signal (to take into account the phase shift introduced by low-pass filtering). RR interval time series were calculated as the time difference between two consecutive R waves.

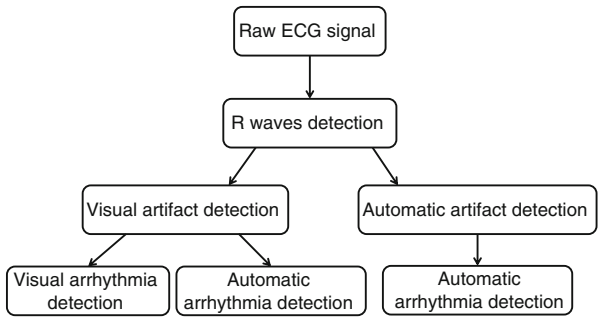

FIGURE 1. Schematic diagram of the different procedures applied to ECG signals.

Artifact Detection

As the algorithm identifying atrial beats relies heavily on the accuracy of RR interval determination, falsely detected R waves had to be discarded before any further analysis. All ECG recordings were visually inspected and misclassified R waves were identified. R waves obtained after removing misclassified R waves were referred to as visual R waves.

For the purpose of a fully automatic procedure, misclassified R waves had to be automatically removed. Most misclassified R waves are due to movement artifacts, and appear as rapid and large variations of the ECG signal, frequently lasting several tenths of a second. During these periods, the filtered ECG is at a higher level (as observed after differentiation) and contains less distinct peaks than during a normal period (Fig. 2). To detect misclassified R waves, two indices were computed for each peak in the filtered ECG signal during the detection of R waves:

- the *amplitude ratio* (*AR*), taken as the ratio between the amplitude of the peak and the median of the five preceding peaks. As we were only interested in the magnitude of the variation and not in its direction, we chose the inverse ratio if the ratio was < 1.
- the *noise level* (*NL*), taken as the ratio between the largest amplitude of the valleys on either side of the peak and the amplitude of the peak (Fig. 2).

Figure 3 plots the values of both indices for every detected R wave from a 24-h ECG recording. Real and misclassified R waves were present in mostly distinct areas of the plot, so that a condition based on both indices could be defined to discard most misclassified R waves and only few real R waves. Based on the distribution of real and misclassified R waves, the inverse curve $AR = (\tau/NL) + 1$ efficiently classified R waves, using a single parameter τ. All R waves above the curve were removed and the corresponding RR intervals were removed from the RR time series. The obtained R waves were referred to as automatic R waves.

For each recording, the value of τ was chosen so as to maximize the performance of the classification in that recording. Performance was defined as the percentage of removed misclassified R waves among all removed and all misclassified R waves. This index takes values between 0 (no misclassified R waves are removed) and 1 (all and only misclassified R waves are removed). The mean of all τ values was used for further analyses.

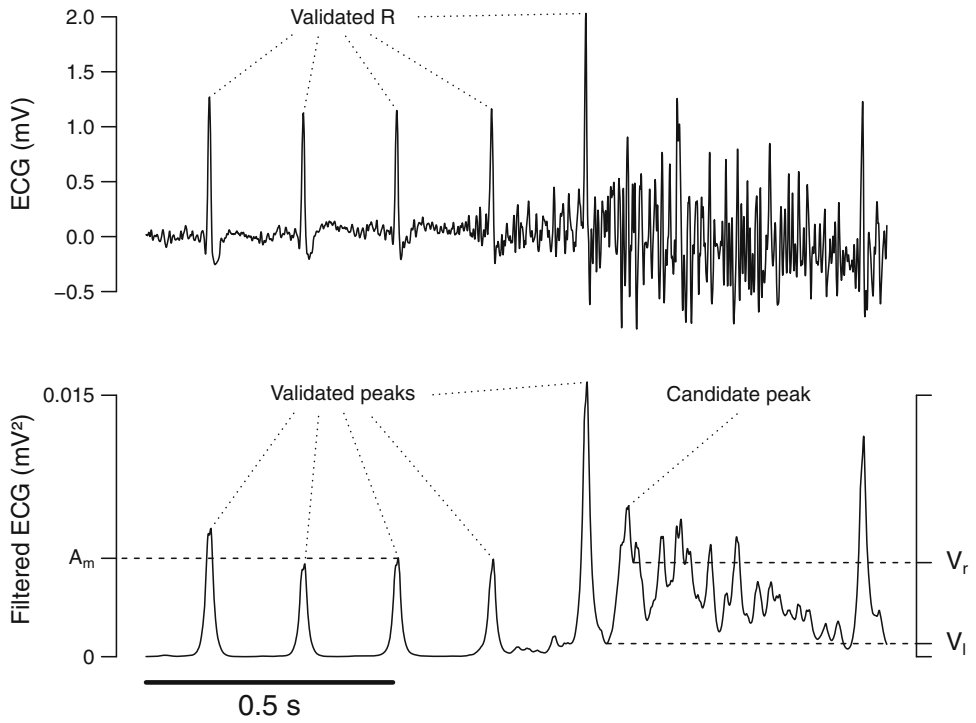

FIGURE 2. Example of detection of misclassified R waves. Raw and filtered 1.5-s ECG signals are shown, along with 5 validated R waves. To validate the next peak on the filtered ECG, the amplitude ratio was computed as the ratio between the amplitude of the peak and the median amplitude of the 5 preceding peaks (A_m), and the noise level was computed as the ratio between the largest amplitude of the valleys on either side of the peak (V_l and V_r) and the amplitude of the peak.

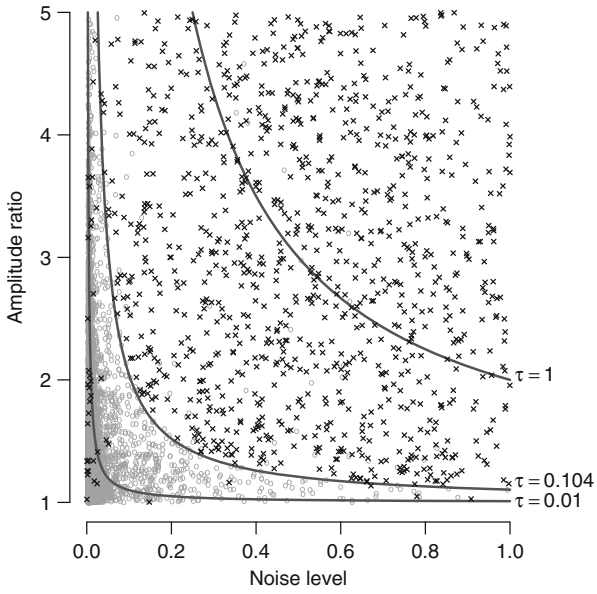

FIGURE 3. Plot of the values of amplitude ratio and noise level for all detected R waves in a 24-h ECG recording. From a 24-h ECG recording, 443,209 R waves were automatically detected, of which 2050 were misclassified R waves and are shown by black crosses. Real R waves are shown by gray open circles. Amplitude ratio (*AR*) and noise level (*NL*) were calculated for every R wave and were plotted. Only *AR* values between 1 and 5 are shown for legibility. The inverse curve $AR = (\tau/NL) + 1$, plotted for three different values of τ (0.01, 0.104 and 1), separates most misclassified R waves from real R waves. For $\tau = 0.104$, 2,008 misclassified R waves are removed (98%), while only 75 real R waves are removed which corresponds to 0.017% of all real R waves.

Visual Arrhythmia Identification

All ECG recordings were visually screened by two experts, one of whom was a cardiologist. Cardiac beats were assigned to three categories: normal, atrial and ventricular beats. Ectopic atrial beats were defined based on the presence of premature, narrow QRS complexes. The definition also demanded that, when visible, atrial waves would be of noticeably different morphology compared to sinus rhythm P waves (Fig. 4). Premature ventricular beats were defined as premature, wide QRS complexes with quite different morphology from sinus beats (Fig. 4).

AT was defined as rapid, irregular, supraventricular rhythm (irregular ventricular response with narrow QRS complexes), of at least 3 beats. Ventricular tachycardia (VT) was defined as rapid ventricular rhythm (enlarged and distorted QRS complexes) of at least 3 beats.

Given that the purpose of this study was to identify atrial and ventricular tachyarrhythmias, other arrhythmic events, such as sinus pauses or atrioventricular blocks, were considered as normal beats.

Ectopic atrial and ventricular beats are referred to as arrhythmic beats in the following text.

Dispersion of Atrial Arrhythmias

The variability of occurrence of ectopic atrial beats was quantified over all 30 ECG recordings. For each 24-h recording, the number of ectopic atrial beats was counted over segments of length l. Each segment was shifted from the previous one by 1 min. The average number of ectopic atrial beats, standard deviation and coefficient of variation (CV) were computed. The mean (±SEM) CV of all recordings was computed with l varying from 1 min to 24 h. To compare against a sequence of randomly occurring ectopic atrial beats, this analysis was performed on the same recordings after ectopic atrial beats had been randomly shuffled following a uniform distribution.

Automatic Arrhythmia Identification

Automatic detection of arrhythmia was performed by using an algorithm based on an automaton structure. This algorithm used the RR interval time series as the only input signal, and labeled each beat as normal (N), arrhythmic (A) or as a compensatory pause (P), i.e., the pause following an arrhythmic beat.

We first introduced a simple deterministic model, which served as the basis of the complete model. In this first model, the label of a beat b was determined based on (i) the label of the previous beat $b - 1$, (ii) the RR interval between beats $b - 1$ and b (RR_b), and (iii) a reference RR interval (RR_n) computed as the median of the five preceding RR intervals between beats labeled as normal. RR_n reflected the current sinus rhythm.

An arrhythmic beat was characterized by a reduction of the RR interval compared to the sinus RR interval. The first rule was, therefore, that if beat $b - 1$ was normal, then beat b was labeled as arrhythmic if $RR_b < k_A\ RR_n$, and normal otherwise, for a certain value of the coefficient k_A. In addition, a tachyarrhythmic event ends with a compensatory pause resulting in a RR interval larger than the sinus RR interval. So, if beat $b - 1$ was arrhythmic, beat b was labeled as a pause if $RR_b > k_P\ RR_n$, and arrhythmic otherwise, for a certain value of the coefficient k_P. A last rule was needed to discriminate tachyarrhythmia from sinus tachycardia. If the last five beats were classified as arrhythmic and the coefficient of variation of the last five RR intervals was lower than a certain value of parameter C, then the whole arrhythmic sequence was changed to normal. A schematic version of this model is illustrated in Fig. 5.

One limitation of this simple model is the use of binary conditions. By converting continuous variables into binary variables, information is lost in the process. Based on this model, we elaborated a more complex

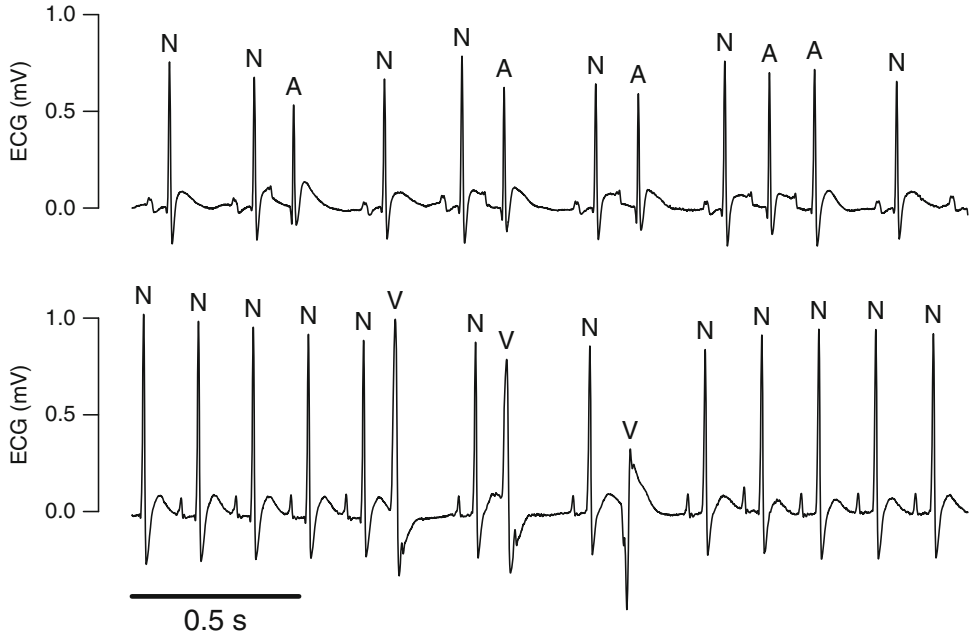

FIGURE 4. Examples of ectopic atrial and ventricular beats. Two 2.5-s ECG recordings from two different rats are shown. Cardiac beats are labeled as normal (N), atrial (A) or ventricular (V).

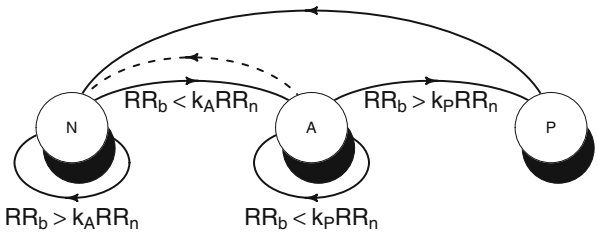

FIGURE 5. Simple automaton model for arrhythmia detection. The three states of the automaton (N, normal; A, arrhythmic; P, pause) are represented as circles, and transitions as arrows. RR_b is the current RR interval, RR_n is the median of the five preceding normal RR intervals, and k_A and k_P are parameters. The dashed arrow represents the case where sinus tachycardia is detected, which is considered as normal beats.

model using probabilities. Every beat b was given probabilities to belong to each state (p_N^b, p_A^b and p_P^b respectively for normal, arrhythmic and pause states). Strict conditions on the first model were replaced by smooth conditions by using the logistic function $H_s(x) = \frac{1}{1+e^{-2sx}}$. This function was characterized by $H_s(x) \approx 0$ for $x \ll 0$ and $H_s(x) \approx 1$ for $x = 0$, with s being the slope of the transition at $x = 0$.

The first rule of the simple model became: $p_N^b|_N^{b-1} = H_s(RR_b - k_A RR_n)$, where $p_N^b|_N^{b-1}$ is the probability that beat b is normal given that beat $b-1$ is normal, and $p_A^b|_N^{b-1} = 1 - p_N^b|_N^{b-1}$. The second rule became $p_P^b|_A^{b-1} = H_s(RR_b - k_P RR_n)$ and $p_A^b|_A^{b-1} = 1 - p_P^b|_A^{b-1}$. It is assumed that $p_N^b|_P^{b-1} = 1$, $p_P^b|_N^{b-1} = p_N^b|_A^{b-1} = p_A^b|_P^{b-1} = p_P^b|_P^{b-1} = 0$

Using conditional probabilities, we derived the formula for p_N^b:

$$p_N^b = p_N^{b-1} p_N^b|_N^{b-1} + p_A^{b-1} p_N^b|_A^{b-1} + p_P^{b-1} p_N^b|_P^{b-1}$$

$$= p_N^{b-1} H_s(RR_b - k_A RR_n) + p_P^{b-1}$$

The other probabilities were computed using the same approach:

$$p_A^b = p_N^{b-1}(1 - H_s(RR_b - k_A RR_n)) + p_A^{b-1}(1 - H_s(RR_b - k_P RR_n))$$

$$p_P^b = p_A^{b-1} H_s(RR_b - k_P RR_n)$$

After determining the probabilities for beat b, we still had to label the beat. We used the following rules:

- if $p_N^b > 0.5$, beat b was labeled as normal. We also set $p_N^b = 1, p_A^b = p_P^b = 0$
- If $p_P^b > 0.5$, beat b was labeled as a pause. We also set $p_N^b = 1, p_A^b = p_P^b = 0$
- Otherwise, beat b was labeled as arrhythmic

The algorithm was initialized as $p_N^b = 1, p_A^b = p_P^b = 0$. In addition, the first five beats were not labeled, and were considered as normal beats to compute RR_n.

Optimization of the Parameters

The previously described algorithm depends on the values of parameters k_A, k_P, s and C. These values

needed to be chosen so as to maximize the performance of the algorithm, estimated by the accuracy (Acc) of the identification, defined as Acc = TP/(TP + FP + FN). TP (true positives) was the number of correctly classified arrhythmic beats, FN (false negatives) was the number of arrhythmic beats classified as normal beats, and FP (false positives) was the number of normal beats classified as arrhythmic beats. Performance indices were given as sensitivity (Se = TP/(TP + FN)) and positive predictive value (+P = TP/(TP + FP)).

Because an exhaustive search for the best accuracy would require testing every combination of values for the 4 parameters, and thus, would be too time consuming, the maximization was performed by the Nelder–Mead method,[10] an optimization algorithm which relies on the evaluation over a small number of sets of parameters.

To correctly estimate the performance of the automatic arrhythmia identification, a strategy had to be carefully chosen. If the same dataset was used for both optimization of the parameters (training set) and evaluation (testing set), the performance would be overestimated as compared with the case where training and testing sets were distinct, which was the case in practice. For each rat, the testing set included all recordings of that rat while the training set included all other recordings. Training was performed using visual R waves. Testing was performed using both visual R waves, to evaluate the performance of the arrhythmia detection, and automatic R waves, to evaluate the performance of the full procedure. Results included sensitivity and positive predictive value, as previously defined.

Emotional Stress Protocol

At the age of 47 weeks, a mild emotional stress was evoked by blowing a jet of air into the cage for 20 min.[13] Only 4 rats could be analyzed due to signal loss in one of the recordings during the stress trial. Artifact detection and arrhythmia identification were performed on the 20-min ECG recordings, using the mean parameters computed earlier.

RESULTS

After visual screening of all ECG recordings, a total of 164,921 misclassified R waves were identified. Using the automatic artifact detection, the mean value of τ was 0.104 ± 0.007 (range 0.037–0.168). Using this value, 141,470 misclassified R waves and 10,671 real R waves were removed, yielding an accuracy of 0.81. This value of τ was used for further analyses.

Using a visual identification of arrhythmias, the total number of ectopic atrial beats was 161,615, ranging from 44 to 49,366 in 24-h recordings. In each rat, the number of ectopic atrial beats increased with age. The median number of ectopic atrial beats was 181 at the age of 26 weeks and 2952 at the age of 46 weeks. In addition, 10,013 AT episodes were identified with a range of 0–4223/24 h. Premature ventricular beats were much less frequent, with a total of 5186 beats and a range of 48–682/24 h, and only 25 VT episodes were identified (range 0–5/24 h). Premature ventricular beats were roughly classified into two groups, either with (29%) or without (71%) an R wave. Both types are shown in Fig. 4.

Occurrence of ectopic atrial beats was highly variable within 24-h recordings, resulting in a high variability in ectopic atrial beats count when restricting to shorter segments (Fig. 6). When considering a CV of 10%, at least 18 h from actual ECG recordings should be analyzed to estimate the total number of ectopic atrial beats, while only 3 h needed to be analyzed in the case of randomly occurring ectopic atrial beats.

Regarding the automatic arrhythmia detection, after the algorithm was trained for each rat, the mean (±SEM) values of the parameters were $k_A = 0.897 \pm 0.002$, $k_P = 0.958 \pm 0.002$, $s = 4.05 \pm 0.26$ ms^{-1} and $C = 3.96 \pm 0.10$. Results of arrhythmia detection for each rat are shown in Table 1 when using visual R waves, and Table 2 when using automatic R waves. The overall

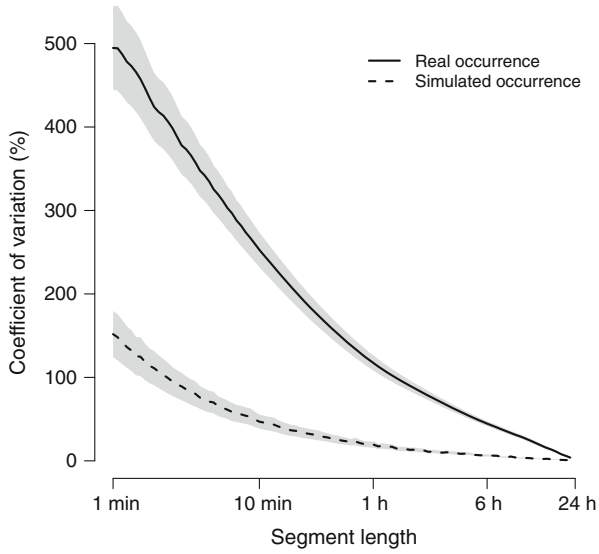

FIGURE 6. Plot of the coefficient of variation of the number of ectopic atrial beats depending on the length of the segment considered. Mean ± SEM were computed over thirty 24-h ECG signals and are shown in grey. The solid line corresponds to the real occurrence of ectopic atrial beats, and the dashed line corresponds to the simulated occurrence after ectopic atrial beats have been randomly shuffled following a uniform distribution.

detection had a sensitivity of 0.91 and a positive predictive value of 0.94 when using visual R waves. When using automatic R waves, the sensitivity was 0.89 and positive predictive value was 0.91.

During emotional stress, 399 of the 445 misclassified R waves and 30 real R waves were removed, yielding an accuracy of 0.84. Using the mean values for each parameter, arrhythmia detection had a sensitivity of 0.88 and a positive predictive value of 0.97.

DISCUSSION

The main result of this study is the description of a fully automatic procedure to detect R waves and to accurately identify AT sequences. This identification solely relies on the RR interval, a robust parameter, which allows analyzing noisy portions of the signal, while a morphology-based analysis would have been strongly affected by noise. The design of the algorithm, which goes through the RR interval time series in one pass, allows a very fast analysis (<10 s for a 24-h ECG recording) making it suitable for online use. Long-lasting recordings can be analyzed using this algorithm, which is all the more important because spontaneous atrial arrhythmias in rats are heterogeneously scattered over time. By selecting small portions of recorded data, as reported in some studies,[7,9] the arrhythmic burden would be misestimated.

A previous study used a standard automaton to detect premature ventricular beats in human RR interval time series.[14] Parameters of the automaton were determined by medical experts, and as such, were not transferable to other species. Other studies used a fuzzy automaton based on the identification of atrial fibrillatory (f) waves to detect atrial fibrillation in humans.[12,15] These waves are absent or hardly visible in the case of AT episodes in rats. A recent study addressed the issue of arrhythmia detection in several species,[7] including the detection of ectopic atrial beats in the rat. However, the number of ectopic atrial beats in the test database was small ($n = 40$) and the detection of ectopic atrial beats was based on a user-specified threshold on RR interval reduction. The authors also reported difficulties in detecting P waves in rat ECG signals, especially due to noise and artifacts.

For detecting R waves, we used a standard derivative-based method, where parameters were easily adapted to the rat ECG characteristics. As our main concern was to accurately detect R waves of atrial arrhythmic beats, methods based on the shape of the QRS complex, such as wavelet-based methods, would have a worse performance on arrhythmic beats. The artifact detection algorithm, based on a single parameter, successfully removed most misclassified R waves. The optimal value of this parameter was steady across all 24-h ECG recordings. Thus, by taking the mean value for all recordings instead of the optimal value, the performance was almost as good.

In the present study, identification of arrhythmic beats when using visual R waves was affected by a small number of false positives and false negatives. False positives were usually encountered during periods of strong respiratory sinus arrhythmia, when variations of RR intervals were high enough to trigger arrhythmia detection. False positives were more rarely seen during reflex tachycardia following sinus pauses or second degree AV blocks. False negatives were mostly due to late ectopic atrial beats, when the reduction of the RR interval was modest.

The accuracy of arrhythmia detection when using automatic R waves was lower than when using visual R waves, due to both more false positives and more false negatives. False positives were mostly ECG artifacts that were not removed by the automatic artifact detection. This artifact detection procedure successfully removed most muscle artifacts as it was designed for that type of artifact. Electrical interferences and loss of ECG signal, although occurring rarely, accounted for a significant part of the remaining

TABLE 1. Performance of the identification of arrhythmic beats using visually detected R waves.

	SHR1	SHR2	SHR3	SHR4	SHR5	Total
Counts						
TP	27,895	26,096	34,942	61,501	1227	151,661
FN	2238	2259	6586	3930	127	15,140
FP	558	861	360	7172	537	9488
Indices						
Se	0.93	0.92	0.84	0.94	0.91	0.91
+P	0.98	0.97	0.99	0.90	0.70	0.94
Acc	0.91	0.89	0.83	0.85	0.65	0.86

For each rat, all six 24-h recordings were pooled. TP: True Positives (correctly classified arrhythmic beats); FN: False Negatives (arrhythmic beats classified as normal beats); FP: False Positives (normal beats classified as arrhythmic beats); Se: Sensitivity; +P: Positive predictive value; Acc: Accuracy.

TABLE 2. Performance of the identification of arrhythmic beats using automatically detected R waves.

	SHR1	SHR2	SHR3	SHR4	SHR5	Total
Counts						
TP	26,540	25,619	33,727	60,898	1005	147,789
FN	3593	2736	7801	4533	349	19,012
FP	1826	2002	1851	8006	1557	15,242
Indices						
Se	0.88	0.90	0.81	0.93	0.74	0.89
+P	0.94	0.93	0.95	0.88	0.39	0.91
Acc	0.83	0.84	0.78	0.83	0.35	0.81

For each rat, all six 24-h recordings were pooled. TP: True Positives (correctly classified arrhythmic beats); FN: False Negatives (arrhythmic beats classified as normal beats); FP: False Positives (normal beats classified as arrhythmic beats); Se: Sensitivity; +P: Positive predictive value; Acc: Accuracy.

undetected artifacts. More false negatives were also found using automatic R waves, but most of them were undetected premature ventricular beats. As the majority of premature ventricular beats had no R waves, they were usually skipped by the R wave detection algorithm and thus could not be automatically detected as arrhythmic beats. On the contrary, ectopic atrial beats were not affected by the automatic artifact removal, as 99.7% of ectopic atrial beats were associated with a validated R wave after that procedure (data not shown).

We used sensitivity and positive predictive value as indices of the performance of the algorithms, instead of the more common sensitivity/specificity. For arrhythmia detection, specificity corresponds to the proportion of normal beats classified as normal, and in our study, it always took very high values (range 0.998–1.000; data not shown), which makes this index irrelevant. We better characterized arrhythmia detection using positive predictive value, which indicates the proportion of true arrhythmic beats among detected arrhythmic beats. Most studies on arrhythmia detection compute the same indices,[5,7] although, as mentioned in Koeppel *et al.*,[7] the positive predictive value is strongly related to the prevalence of arrhythmia in ECG recordings. In the present study, the rat SHR5 showed very few arrhythmic beats compared to the other rats and the positive predictive value was much lower in this rat. This can be explained because the number of false positives, typically around 100 for a single 24-h recording, mainly due to artifacts, does not depend on the number of arrhythmic beats.

The main limitation of this method is its inability to discriminate between ectopic atrial and ventricular beats, as it is solely based on RR intervals. Accurate recognition of ventricular beats would have required a morphology analysis (i.e., the estimation of the width of the QRS complex). Although ventricular beats were present in every recording, VT episodes were very rare. Thus, by focusing on arrhythmic sequences of 3 beats and more, we ensured to almost only target atrial tachyarrhythmia. It should be mentioned, however, that the performance of the algorithm in the presence of atrial fibrillation, *stricto* sensu, could not be evaluated in this study.

The full algorithm was also tested during an emotional stress induced by a jet of air. This protocol is known to increase the sympathetic tone,[4] leading to a higher heart rate. In addition, more ECG artifacts were present due to movements of rats. Under this condition, both the artifact detection and arrhythmia identification procedures showed similar performance compared to baseline recordings.

In conclusion, we propose an efficient method to automatically detect tachyarrhythmia in long-lasting ECG recordings from aging SHRs. This algorithm is based on RR intervals, which allows an accurate detection even from noisy signals.

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