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Accuracy of algorithms for detection of atrial fibrillation from short duration beat interval recordings

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ABSTRACT

Atrial fibrillation (AF) is characterised by highly variable beat intervals. The aims of the study were to assess the accuracy of AF detection algorithms from short analysis durations and to validate prospectively the accuracy on a large community-based cohort of elderly subjects. Three algorithms for AF detection were evaluated: coefficient of variation (CV), mean successive difference (Δ) and coefficient of sample entropy (COSEn), using two databases of beat interval recordings: 167 recordings of 300 s duration for a range of rhythms acquired in a hospital setting and 2130 recordings of 10 s duration acquired in the community. Using the longer recordings receiver operating characteristic (ROC) analysis was used to identify optimal algorithm thresholds and to evaluate analysis durations ranging from 5 s to 60 s. An ROC area of 93% was obtained at recording duration of 60 s but remained above 90% for durations as low as 5 s. Prospective analysis on the 2130 recordings gave AF detector sensitivities from 90.5% (CV and Δ) to 95.2% (COSEn), specificities from 89.3% (Δ) to 93.4% (COSEn) and accuracy from 89.3% (Δ) to 93.4% (COSEn), not significantly different to those obtained on the initial database. AF detection algorithms are effective for short analysis durations, offering the prospect of a simple and rapid diagnostic test based on beat intervals alone.

1. Introduction

Atrial fibrillation (AF) is the most common sustained arrhythmia affecting more than 6 million people in Europe and 3 million people in the US [1–3]. The true prevalence of AF is however unknown because in many patients the condition is asymptomatic and remains undetected [4]. AF is most prevalent in the elderly having been described as an emerging epidemic and the number of cases is set to more than double by 2050 due to an aging population [1,5–7]. AF is a major risk factor for stroke and accounts for an estimated 15% of all strokes. Stroke due to AF is more likely to be fatal and to lead to more severe disability than stroke due to other causes [8,9]. Stroke risk is substantially reduced by AF therapy which aims to restore the normal heart rhythm or manage the thrombotic risk with medication [10]. Consequently there are significant benefits for patients and healthcare systems around the world if AF can be detected and stroke preventative measures applied.

AF is characterised by highly variable ventricular beat intervals [11]. Clinicians have used this observation for many years to effectively diagnose AF manually by pulse palpation achieving sensitivity above 90% and specificity above 70% [12,13]. Opportunistic pulse palpation by family doctors for all patients 65 years and older is the current recommended AF screening strategy in the UK [14]. As ectopic beats in sinus rhythm increase uncertainty in detection of AF, suspected AF due to palpation of an irregular pulse is normally confirmed by electrocardiogram (ECG). Beat interval variability forms the basis of several algorithms for automatic detection of AF [15–21]. There is a growing opportunity for automated AF detection with the phenomenal growth in the use of home-based healthcare monitoring devices such as personal ECG and blood pressure monitors. Additionally, there is increasing availability of smart phone technology for heart monitoring that includes simple pulse detection from which beat intervals can be obtained. Uptake

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of these new technologies is dependent upon convenience and ease of use, so from this perspective the shorter the monitoring period the more acceptable would be the technology to the user. Regular pulse/beat interval checks of short duration, for example, a few seconds, are more likely to be regularly undertaken than monitoring periods extending into minutes. A recent study indicated that accurate detection of AF could be achieved using very short lengths of beat intervals with the intended application to rhythm discrimination in implanted ventricular devices [20]. Area under the receiver operating characteristic (ROC) curve of >90% was achieved with an algorithm applied to beat intervals from only 12 consecutive beats. However, the effect of ectopic beats needs to be carefully considered as these are known to confound the accurate detection of AF. Beat intervals containing ectopic beats can mimic the irregular beat pattern typical of AF. For this reason ectopic beats are often removed as a pre-processing stage of many ECG based AF detection algorithms. The detection of ectopic beats may not be possible for other modes of beat interval measurement, so the accuracy of the algorithms in the presence of ectopic beats needs to be established. Here we are not considering algorithms which necessitate ECG measurements, for example, those which detect AF by the absence of P waves. Additionally, we make no assumption about the origin of the beat interval data that could be from ECG, blood pressure device or other devices capable of measuring beat intervals. The aims of this study were twofold: 1 to quantify the accuracy of automated AF detection from short duration beat interval recordings and 2 to validate prospectively the accuracy on a large database of short duration beat interval recordings from a community based population.

2. Methods

2.1. Beat interval recordings

Beat intervals for this study were derived from two databases of ECG recordings. Database 1 (DB1) was used to investigate the effect of beat interval recording duration on accuracy of AF detection and to determine optimum algorithm thresholds. Database 2 (DB2) was used to validate prospectively the accuracy of the algorithms.

2.1.1. Database for assessing analysis duration and algorithm optimisation

The first database (DB1) comprised ECG recordings from 167 subjects with a range of cardiac rhythms collected in the Freeman Hospital, Newcastle upon Tyne, UK. ECGs were grouped according to type of rhythm: AF ($n = 55$), sinus rhythm (SR, $n = 72$), sinus rhythm with ectopic beats (Ect, $n = 27$) and other rhythms (Other, $n = 13$) including paced rhythms and atrial flutter. ECGs rhythms were expertly classified by the clinician at the time of the recording and subsequently validated by one of the researchers (PL). All recordings were of 300 s duration and stored digitally at a sample rate of 500 Hz and amplitude resolution of 5 μV.

2.1.2. Database for prospective validation

The second database (DB2) comprised ECG recordings from a community-based cohort of 2124 subjects of age 70 years and above from the Hai district of Northern Tanzania. The ECGs were acquired as part of a study designed to assess the prevalence of AF in this community. The database included 6 follow-up recordings from 6 patients with AF and these were not excluded from the analysis so in total 2130 recordings were analysed. The ECGs were recorded using the GE MAC 1200™ (GE Healthcare, UK), were of 10 s duration and were stored digitally at a sample rate of 500 Hz and amplitude resolution of 5 μV. The ECGs were expertly classified as AF or non-AF at the time of the recording and subsequently independently validated by a researcher (MD). ECGs were downloaded from the ECG machine in XML format for subsequent beat interval calculation.

Subjects gave informed consent and the study was granted ethical approval by the National Institute for Medical Research in Tanzania.

2.1.3. Beat interval calculation

Beat intervals (RR intervals) were calculated using a QRS detection algorithm that applied a threshold to the differential of the ECG lead to determine beat occurrence. Beat intervals were validated by visual inspection of detected beat points, with confirmation of the accurate detection of all beats including ectopic beats. In DB1, sinus rhythm recordings with at least one ectopic beat were analysed as a separate group (Ect) and beat intervals from ectopic beats were not removed from the beat interval time series.

2.2. AF detection algorithms

Three AF detection algorithms were evaluated as described below. Selection of the AF detection algorithms was based on those that use beat intervals alone for AF detection. Algorithms requiring analysis of beat interval time-series longer than the short durations evaluated in this study, for example because of requiring a minimum number of beats, were excluded. The algorithms were selected as being representative of the range of algorithms available from the literature that use different methods of quantifying beat interval variability. Coefficient of variation (CV) is one of the most widely reported algorithms and quantifies beat interval variability as the standard deviation of all analysed beats [18,20]. In contrast, mean successive beat interval difference (Δ) quantifies the beat-to-beat variability [15,18]. Unlike the abovementioned algorithms an entropy based algorithm, COSEn, quantifies the regularity of beat interval patterns [20]. They all use the knowledge that in general beat intervals are more variable and on average shorter (due to faster heart rate) in AF compared to other rhythms.

Defining a vector of beat intervals, $x = [x_1, x_2, x_3, \ldots, x_n]$, where n is the number of beats in the recording with mean interval μ and standard deviation σ, the AF detection algorithms were defined as:

(i) Coefficient of variation (CV)

CV was defined as the standard deviation of the beat intervals divided by the mean beat interval

$$\mathrm{CV} = \frac{\sigma}{\mu}$$

(ii) Mean successive beat interval difference (Δ)

Δ was defined as the mean absolute successive beat interval difference divided by the mean beat interval

$$\Delta = \frac{1}{\mu} \cdot \frac{1}{n-1} \cdot \sum_{i=1}^{n-1} |x_i - x_{i+1}|$$

(iii) Coefficient of sample entropy (COSEn)

Sample entropy is an estimate of entropy and is used to quantify the regularity of a data sequence. In our application it measures the regularity of the beat intervals. COSEn is an entropy based AF detection algorithm that was designed to be effective for short duration recordings and developed for implementation in implantable devices [20]. COSEn is defined as

$$\mathrm{COSEn} = -\ln\left(\frac{A}{B}\right) - \ln(2r) - \ln(\mu)$$

A and B are calculated using the following steps:

(i) Form vectors $X(1), \ldots, X(n-m+1)$ of m consecutive beat intervals: defined by $X(i) = [x(i), x(i+1), \ldots, x(i+m-1)]$, for $1 \le i \le n-m+1$.
(ii) The maximum absolute difference between vector scalar components, $d[X(i), X(j)]$, determines the distance between the vectors:

$$d[X(i), X(j)] = \max_{k=1,2,\ldots,m} (|x(i+k) - x(j+k)|)$$

(iii) For each $X(i)$ count the number of matches where $d[X(i), X(j)] \le r$, $(j \neq i)$.

A and B denote the total number of beat interval patterns of length $m+1$ and m respectively, that match within a given tolerance r. We used the parameters specified by Lake and Moorman which optimise COSEn for short analysis duration, so $m=1$ and r was initialised to 30 ms but was allowed to increase in 5 ms steps until the minimum numerator count (A) was 5 or greater [20].

Detection of AF by each of the algorithms is based on the algorithm index (CV, Δ and COSEn) exceeding a given threshold. Thresholds were determined by ROC analysis on DB1 described below.

2.3. Effect of beat interval recording duration on AF detection accuracy

2.3.1. Segmentation of beat intervals to simulate recording lengths from 5 to 60 s

The first part of the study was to assess the effect of recording duration on AF detection accuracy. From the 300 s recordings from DB1, beat interval time-series of durations of 5 s, 10 s, 15 s, 20 s, 30 s and 60 s were extracted. The 300 s recordings were segmented into contiguous segments of lengths 5 s, 10 s, 15 s, 20 s, 30 s and 60 s. This provided for each subject 60, 30, 20, 15, 10 and 5 segments for each extracted recording duration respectively. In the subsequent analysis all segments for all subjects were analysed. The algorithm indices for each of the AF detection algorithms were calculated for each beat interval segment. Thresholds to maximise detection accuracy were determined from ROC analysis described below.

2.3.2. Receiver operating characteristic analysis

The receiver operating characteristic (ROC) curve shows the relationship between specificity and sensitivity of a classifier over a range of thresholds. From the ROC curve the optimum threshold can be identified as the point on the curve with shortest distance to the point corresponding to sensitivity and specificity of 1. Additionally, a useful measure for comparing the accuracy of classifiers is the area under the ROC curve (ROC area) that tends to 1 for the most accurate classifiers. An ROC curve was produced for each beat interval segment across all subjects giving multiple ROC curves for each analysis duration. ROC area and optimum threshold were calculated from each ROC curve and mean and standard deviation of area and threshold calculated. This was done separately for AF vs each rhythm group (SR, Ect, Other) for each AF detection algorithm.

2.4. Prospective validation of AF detection algorithm accuracy

DB2 was used for prospective validation of the accuracy of AF detection for a beat interval recording duration of 10 s. From the analysis of the DB1 we knew the optimum threshold for each analysis duration, rhythm group and algorithm. Therefore, the optimum thresholds for an analysis duration of 10 s were applied to the beat intervals for DB2. The numbers of cases correctly classified as AF (TP), incorrectly classified as AF (FP), correctly classified as non-AF (TN) and incorrectly classified as non-AF (FN) were recorded and the specificity (TN/(FP + TN)), sensitivity (TP/(TP + FN)) and accuracy ((TP + TN)/(TP + FN + FP + TN)) of AF detection were calculated and compared with those from DB1.

Table 1
Mean (sd) of CV, Δ and COSEn for AF vs other rhythms combined from DB1. The mean value was calculated for each subject and the mean and standard deviation (sd) reported for AF group and non-AF group. Statistical differences between groups were analysed using two-sample t test ($\alpha = 0.05$).

	AF ($n=55$)	Other rhythms ($n=112$)	Confidence interval of difference
CV	0.225 (0.010)	0.048 (0.004)	(0.175–0.179)
Δ	0.252 (0.011)	0.040 (0.006)	(0.210–0.215)
COSEn	−0.414 (0.049)	−1.881 (0.064)	(1.448–1.486)

2.5. Statistical analysis

Two-way ANOVA was used to assess differences with respect to duration and rhythm of mean values of indices, AUC and threshold. Two-sample t test ($\alpha = 0.05$) was used to assess differences in AF detection algorithm indices (CV, Δ and COSEn) between AF and non-AF rhythms, differences in ROC area for recording durations of 5 s and 60 s, and differences in sensitivities, specificities and accuracies between databases.

3. Results

3.1. Effect of recording duration and rhythm category on AF detectors

3.1.1. Algorithm indices

Fig. 1a provides summary data for the algorithm indices from DB1 according to simulated recording duration and rhythm category. For all algorithms ANOVA indicated significant differences between mean values of algorithm indices for both durations and rhythms. Mean values of indices increased as duration increased reflecting the greater degree of beat variability captured by longer recording durations. As expected indices were significantly higher for AF compared to non-AF rhythms (Table 1).

3.1.2. ROC area

Fig. 1b provides summary data for the ROC area analysis. For all algorithms mean area increased as recording duration increased, indicating that algorithms performed better at longer recording durations. ANOVA indicated significant differences in mean area across durations for all algorithms. Across all algorithms there was a significant increase in area from 90.7% to 94.0% when increasing recording duration from 5 s to 60 s (Table 2).

ANOVA also indicated significant differences in mean ROC area across rhythms for CV and Δ, but not for COSEn. Area was greatest

Table 2
Mean (sd) ROC area (%) for AF vs all non-AF rhythms for durations of 5 s and 60 s. Statistical differences between analysis duration of 5 s and 60 s were analysed using two-sample t test ($\alpha = 0.05$).

Algorithm	5 s ($n=60$)	60 s ($n=5$)	Confidence interval of difference
CV	90.8 (1.3)	93.9 (1.3)	(1.9–4.3)
Δ	91.2 (1.3)	93.4 (0.8)	(1.1–3.4)
COSEn	90.2 (1.6)	94.6 (0.6)	(3.0–5.8)
All	90.7 (0.5)	94.0 (0.6)	(2.0–4.5)

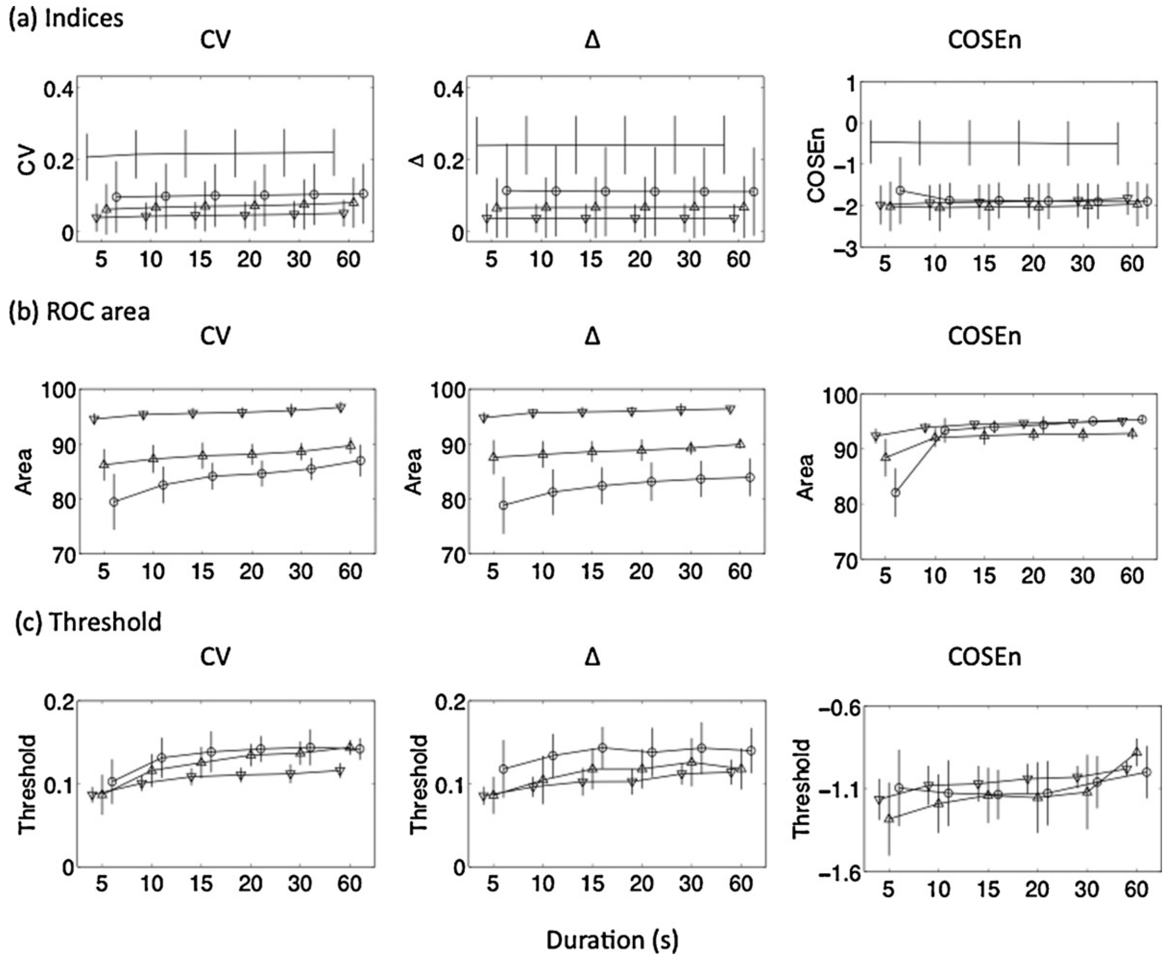

Fig. 1. (a) Algorithm indices (CV, Δ and COSEn), (b) ROC area (%) and (c) optimum threshold for analysis duration and rhythm category from DB1. ROC area and threshold are shown for rhythm groups SR, Ect and Other with respect to AF group. Mean and standard deviation are indicated. Line markers indicate rhythm group (▽, SR; △, Ect; ○, Other; no marker, AF).

for differentiating AF from SR confirming the expected result that the algorithms were better able to discriminate AF from SR.

3.1.3. Threshold

Reflecting the changes in indices values over changes in recording duration there were significant differences in thresholds across durations and rhythms. Specifically, ANOVA indicated significant differences across durations for all algorithms and across rhythms for all but COSEn. Fig. 1c provides summary data for the algorithm thresholds according to rhythm category and recording duration.

3.2. Prospective validation of accuracy of AF detection on DB2

For prospective application of the algorithms to DB2, it was necessary to specify the algorithm thresholds for the specific recording duration of 10 s and the expected rhythm category for the study population. A high probability of ectopy was expected in this study group due to the age of the subjects. Therefore the thresholds used were the mean optimum thresholds for differentiating AF from the ectopic rhythm group (Ect) for a recording duration of 10 s (Table 3). The human classifier of the ECGs identified 21 AF recordings from 15 subjects. The database included follow-up recordings in 6 patients identified as having AF. Table 3 compares the specificity, sensitivity and accuracy of the algorithms applied to both DB1 and DB2 with these thresholds. Comparing mean values across algorithms for each database there were no significant differences between databases for mean (sd) sensitivity (DB1 94.6% (0%) vs DB2 92.1% (2.7%), CI [−1.8% to 6.9%]), specificity (DB1 92.3% (1.0%) vs DB2 90.8% (2.3%), CI [−2.5% to 5.6%]) and accuracy (DB1 93.0% (0.7%) vs DB2 90.8% (2.3%), CI [−1.6% to 6.1%]).

Fig. 2 compares algorithm indices for AF and non-AF rhythms for the two databases. There were no significant differences between indices for the AF rhythm but significant differences for the non-AF rhythms. Indices values for non-AF rhythms were less in DB2 suggesting that DB2 contained a greater proportion of SR cases.

Fig. 3 provides illustrative examples of the cases from DB2. The figure shows the beat interval time-series and ECG lead V1 for 6 cases: on the left, three of AF (a, b and c); and on the right, three of non-AF (d, e and f). Case (a) demonstrates highly variable beat intervals of AF and was accurately identified by all algorithms (COSEn = −0.753, Δ = 0.159, CV = 0.146). Case (b) shows less variability but was accurately identified by COSEn due to the irregular beat interval pattern (COSEn = −0.949, Δ = 0.090, CV = 0.115). Case (c) shows high variability but a repetitive beat interval pattern that was accurately identified by all algorithms

Table 3
Comparison of performance measures of AF detection algorithms for DB1 and DB2.

Algorithm	Threshold	Sensitivity (%)		Specificity (%)		Accuracy (%)	
		DB1	DB2	DB1	DB2	DB1	DB2
CV	0.12	94.6	90.5	92.9	89.6	93.4	89.6
Δ	0.11	94.6	90.5	91.1	89.3	92.2	89.3
COSEn	−1.19	94.6	95.2	92.9	93.4	93.4	93.4

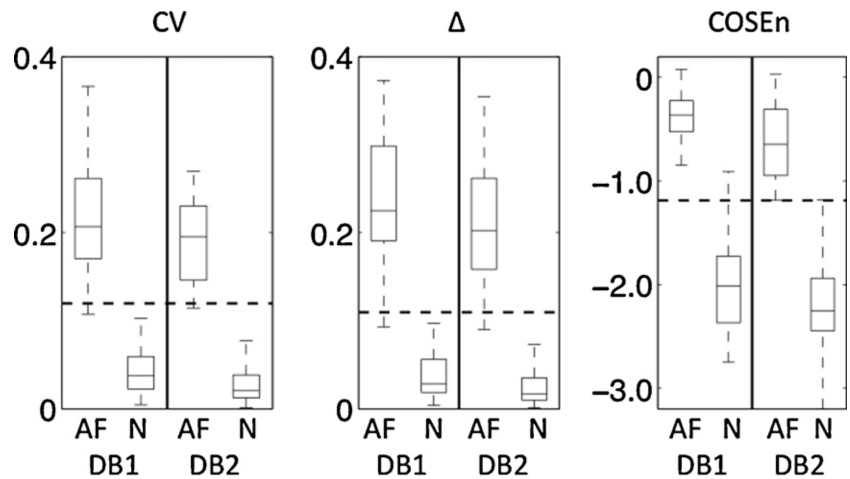

Fig. 2. Algorithm indices CV, Δ and COSEn for AF and non-AF (N) rhythms in databases DB1 and DB2. Dashed line indicates threshold value with indices above the line classed as AF and values below the line classed as non-AF. Boxplots indicate median, interquartile range (box) and range of values lying within 1.5 times the interquartile range (whisker).

except COSEn (COSEn = −1.212, Δ = 0.130, CV = 0.126). Cases (d)–(f) were all falsely classified as AF by all algorithms. Case (d) shows an example with an atrial ectopic beat (COSEn = −1.085, Δ = 0.177, CV = 0.168). Case (e) shows a fast, highly variable non-AF rhythm (COSEn = −0.573, Δ = 0.222, CV = 0.158). Case (f) shows coupled ventricular ectopic beats (COSEn = −0.901, Δ = 0.462, CV = 0.252).

4. Discussion

There is great interest in simple diagnostic tests for detection of AF due to the huge healthcare burden of AF related stroke and heart failure. A diagnostic test based on only a few cardiac beat intervals might have the potential to fulfil this need. The high

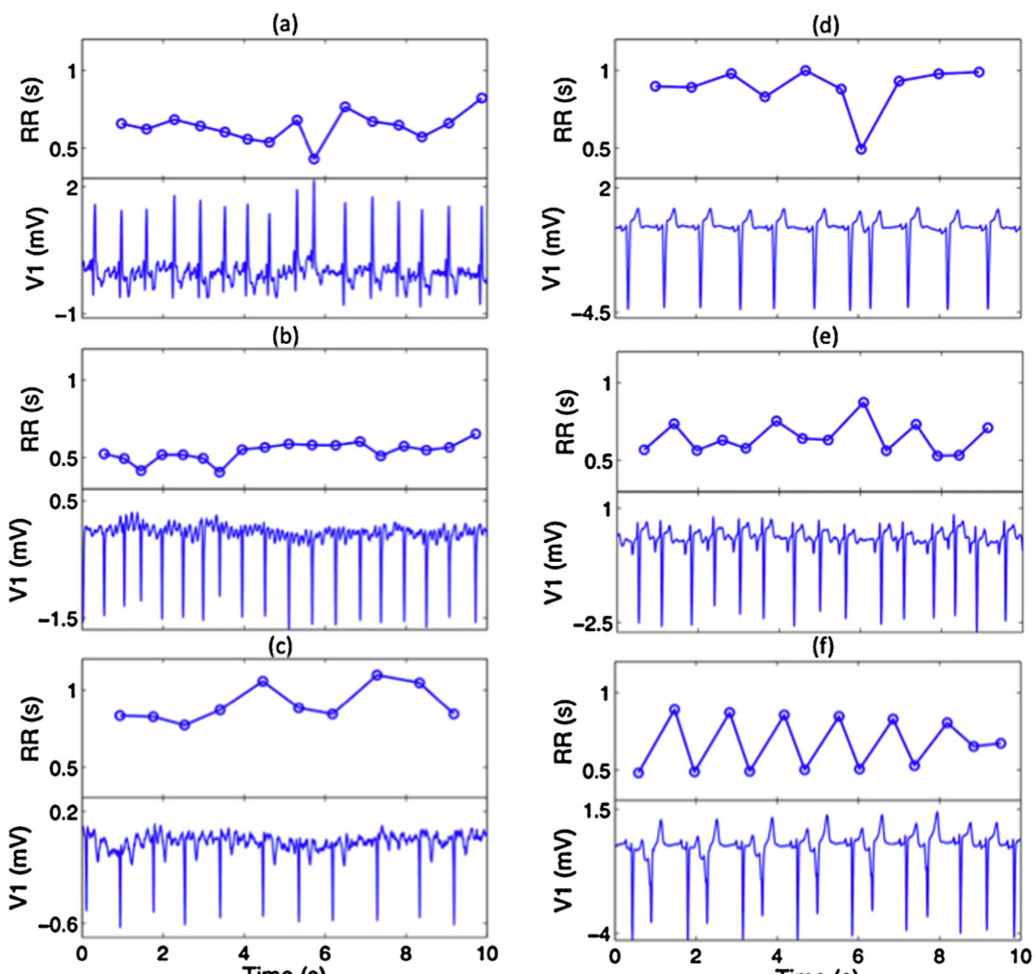

Fig. 3. Beat intervals (RR) and associated ECGs of 6 illustrative recordings. Left panel shows AF cases, right panel shows non-AF cases. Further details are provided in the text.

variability and increased rate of beat intervals in AF ensures AF detection based on these features is highly effective. However, previous studies have focused on detection of AF episodes from long duration recordings with, for example, the aim of detecting AF episodes in long term Holter monitoring. With a view to minimising the length of monitoring period required for a diagnostic test, the motivation for the present study was to evaluate the relationship between length of beat interval recording and accuracy of AF detection. The results show that for a recording duration of only 10 s, sensitivities of greater than 94% and specificities of around 93% were achieved. Performance of the automatic algorithms compares favourably with manual AF detection by pulse palpation with reported sensitivity of 94% and specificity of 72% [22]. Automatic detection algorithms assessed on the long duration recordings of the MIT-BIH databases achieve sensitivities and specificities of up to 96% and 98% respectively [15]. Not all algorithms were suitable for inclusion in our study because they required analysis durations longer than those considered in our study, for example, because they require a minimum number of beats. Our results demonstrate the modest increases in algorithm accuracy achieved (as measured by ROC area) by increasing recording duration. An increase in recording duration from 5 s to 60 s, a 12-fold increase, achieved only a 3% increase in ROC area. However the specific application of the AF detection needs to be considered when choosing a sufficient recording duration and our analysis provides an indication of the relative trade off between recording duration and detection accuracy. Recording durations less than 5 s are impractical since at low heart rates there would be insufficient beats to determine the algorithm indices.

Our study considered the effectiveness of AF detection within specific cardiac rhythm groups and it was shown that the presence of ectopic beats or other abnormal rhythms reduced the performance of all algorithms. As would be expected ectopic beats in sinus rhythm recordings increased beat interval variability so the algorithms based on variability (CV, Δ) were less effective at discriminating AF from these recordings. Typically, ROC area decreased by around 10% relative to sinus rhythm without ectopic beats for these algorithms. Ectopic beats affected beat regularity to a lesser extent and ROC area for COSEn was reduced by less than 5%. Detection performance of COSEn showed less dependance on rhythm category than the other algorithms and had the advantage that its threshold was invariant to cardiac rhythm group. This is an important consideration when, as would be the case practically, the underlying rhythms of the population under test are unknown. COSEn has recently been introduced with the specific application for rhythm discrimination in implanted ventricular devices where storage capacities are limited and was shown to be effective with intervals from just 12 beats [20]. Our study adds to the evidence that COSEn is robust detector in the presence of ectopic beats and for detection of AF from non-SR beat rhythms.

Detection of undiagnosed, asymptomatic AF is a major goal in stroke prevention. With the growing use of home-based health monitoring there is opportunity to add AF detection capability to these devices. Automated AF detection algorithms have already been embedded into home-based blood pressure monitors [23,24]. For such applications it is important to know how analysis duration affects detection accuracy which is directly addressed by our study.

Detection of AF is particularly important in the elderly due to increased prevelance with age [3,25]. A major part of our study was to prospectively validate the effectiveness of AF detection in a large elderly community based population. Prospectively, the algorithms showed good agreement with the retrospective analysis, with very simlar values of sensitivity, specificity and accuracy obtained from both databases. AF recordings in DB1 were from patients admitted to our hospital for AF therapy. Inevitably, some of these patients would be taking anti-arrhythmic drugs. Since drug therapy could reduce beat interval irregularity, it is possible that accuracy of AF detection would be decreased with these patients. DB2 was from a rural, North African population with little access to health care and we are confident that these patients are relatively free of anti-arrhythmic drugs. So it is reassuring that the accuracy of the algorithms is very similar in both databases. In the community, AF can be detected from short beat interval recordings with an accuracy greater than 93%.

5. Conclusion

AF detection algorithms are effective for short duration beat interval recordings, offering the prospect of a simple and rapid diagnostic test based on beat intervals alone.

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Conflict of interest

None.

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