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IJIE

Journal homepage: http://penerbit.uthm.edu.my/ojs/index.php/ijie
ISSN : 2229-838X e-ISSN : 2600-7916

The International Journal of Integrated Engineering

Investigating Phase Space Reconstruction of ECG for Prediction of Malignant Ventricular Arrhythmia

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DOI: https://doi.org/10.30880/ijie.2020.12.02.022
Received 29 December 2019; Accepted 27 January 2020; Available online 28 February 2020

Abstract: Prediction of malignant ventricular arrhythmia is imperative to enable early diagnosis and prevent sudden cardiac death. There are a wide variety of methods employed in previous works with box counting of phase space reconstruction diagrams achieving the highest performance. However, there is no follow-up work investigating or improving this method. This work is performed to objectively assess the feasibility of box counting technique for prediction of malignant ventricular arrhythmia and to validate the prediction technique across larger data sets, including the widely acceptable MIT-BIH database. Box counting using different windowing methods, data representation methods of phase portrait and testing database are investigated for performance and versatility. By using windows of RR segments and linking phase portraits, this modified box counting method has higher resistance to signal noises, which are common in the electrocardiogram. It is verified using four Physionet databases (CUDB, SDDB, PTBDB and NSRDB) which contain either arrhythmic or control records. High prediction accuracy of 94.12%, sensitivity of 88.46% and specificity of 100% are achieved by the coefficient of variation derived from this method. This technique is proven useful in predicting malignant ventricular arrhythmia and its implementation is envisaged to enable early detection and diagnosis.

Keywords: Electrocardiogram (ECG), prediction, ventricular arrhythmia (VA), sudden cardiac death (SCD), phase space reconstruction (PSR), box counting.

1. Introduction

According to World Health Organization, cardiovascular disease causes 17.7 million deaths annually [1]. Sudden cardiac death (SCD) accounts for half of the death caused by cardiovascular disease while malignant ventricular arrhythmia (mVA) causes 80% of SCD [2], [3]. Malignant ventricular arrhythmia is life-threatening arrhythmia originating from ventricles, comprising of ventricular tachycardia and ventricular fibrillation. It is vitally important for the patient to receive prompt medical intervention when mVA occurs for prevention of SCD. Prediction of imminent mVA in advance is even better, by enabling earlier attention to the problems or allowing more time for preventive measures. Hence, there have been a number of researchers investigating electrocardiogram (ECG) changes preceding the mVA events which could be precursor of imminent mVA.

Based on literature review, heart rate variability (HRV) have been studied the most as a prognostic feature for prediction of imminent mVA [4], [5]. Various approaches in time, frequency, time-frequency and nonlinear domain were employed [6]–[11]. Recently, more features were extracted, such as homogeneity index of wavelet-transformed

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ECG [12], pattern of approximate entropy of EMD reconstructed T-Wave [13], statistical measures of box count of phase space plot [14] and so on. Although the current ECG features seemed to provide a reasonable amount of useful information regarding the occurrences of mVA, previous studies showed confounding results on the predictive power of HRV [4], [15] while the other features were comparatively new and need to be further investigated.

Among the previous works on mVA prediction, box counting method of phase space reconstruction (PSR) employed in [14] reported superior performance of 98.44% accuracy, 96.88% sensitivity and 100% specificity. The result implied the potential usage of nonlinear dynamic techniques for prediction of imminent mVA. However, this method was relatively new in prediction work and was only tested with PTBDB as the control database, using 32 subjects' ECG segments. This database was without standard annotation and was not widely used database distributed by MIT-BIH laboratory, making it hard to verify and benchmark the reported performance of this algorithm. Even the authors [14] recommended to conduct testing with a larger database to further examine its predictive power. Anas et al. [16] also pointed out the higher possibility of misclassification of mVA from other arrhythmia using PSR technique while the authors discarded certain mVA records due to signal noises in the study.

Nonetheless, box counting method of PSR could be potentially useful for prediction of imminent mVA, despite that no studies further improved, examined or even utilised this technique for mVA prediction. Hence, our work is aimed to further investigate and improve this technique by (1) altering windowing and data representation of phase portrait in box counting method and identify the prediction performance after modification (2) verify the versatility of this technique by testing against more databases with standard annotation. We intend to identify the reliability and possible improvement of this technique, besides enabling future benchmarking against other works.

2. Methodology

Phase space reconstruction was used to examine the nonlinear dynamics and random behaviour in time series data using phase space diagram. By inserting k time delay (τ) to a time series data, k-dimensional phase space diagram was constructed [17]. In this work, only two-dimensional phase space diagram, named phase portrait, was used. One of the ways to extract information from phase portrait was box counting [18], where box count was used to estimate the degree of complexity of the signal [19]. While box count gave an estimation of signal complexity, statistical analysis of box count helped to characterise the complexity and to identify the underlying desynchronisation phenomenon of ECG signal. In this work, descriptive statistics including coefficient of variation and *kurtosis* were explored. Coefficient of variation (*CV*) was the ratio of standard deviation (σ) to mean (μ), which described the relative dispersion of a time series data. *Kurtosis* (κ) was the fourth standardised statistical moment, which described the tail extremity of the probability distribution of a time series data [20].

2.1 Data

Four databases from Physionet were used in this study. Pre-mVA signals were acquired from Creighton University Ventricular Tachyarrhythmia Database (CUDB) and Sudden Cardiac Death Holter Database (SDDB) while control signals were acquired from Physikalisch-Technische Bundesanstalt Diagnostic ECG Database (PTBDB) and MIT-BIH Normal Sinus Rhythm Database (NSRDB). CUDB comprises 35 eight-minute ECG records from subjects who experienced sustained ventricular tachycardia, ventricular flutter, and ventricular fibrillation. According to [14], ‘CU21’, ‘CU33’ and ‘CU35’ were corrupted with excessive signal noises and hence they were discarded in our study to enable direct comparison of analysis results. SDDB contains 23 Holter ECG records from subjects with sustained ventricular arrhythmia. Three records from SDDB without annotation of VF onset time (‘40’, ‘42’, ‘49’) were discarded. PTBDB contained 52 ECG records from healthy subjects and the same 32 PTBDB records that were included in [14] were used for analysis. NSRDB comprised 18 ECG records from subjects without significant arrhythmia respectively and all of them were used for analysis.

For prediction purpose, ECG signal before mVA onset was extracted from each record of CUDB and SDDB before being used for analysis, as depicted in Fig. 1. ECG records in SDDB were long recordings lasting around 24 hours, while only 10-minute ECG signal before onset of each record was used in this study for the examination of feature. ECG records in CUDB were short recordings lasting around eight minutes and the whole signal before onset of each record was used in this study.

There were multiple lead signals in PTBDB and lead I signal was chosen for analysis in this work to enable comparison with the previous studies in [14]. NSRDB signals used for analysis were starting from the first annotated normal beats after QRS-like artefacts. Besides, ECG records in NSRDB were long recordings lasting around 24 hours, while only 10-minute ECG signal of each record was used in this study for examination of the feature. Standard annotations in the database were used to identify the onset of mVA in CUDB and QRS-like artefacts in NSRDB.

2.2 Procedure

Fig. 2 shows the complete workflow to carry out the prediction of mVA in this work. ECG signals in CUDB, SDDB, NSRDB and PTBDB were recorded at sampling frequency of 250 Hz, 250 Hz, 128 Hz and 1000 Hz respectively. To enable fair comparison, signals in CUDB, SDDB and NSRDB were upsampled to 1000 Hz. After the upsampling, all ECG signals were filtered using fourth order Butterworth filter with passband ranging from 1 Hz to 30 Hz [14] to remove baseline wandering and high-frequency measurement noise. The R peaks of ECG signals were detected using Hamilton-Tompkins algorithm [21], [22] which was enhanced version of Pan-Tompkins algorithm.

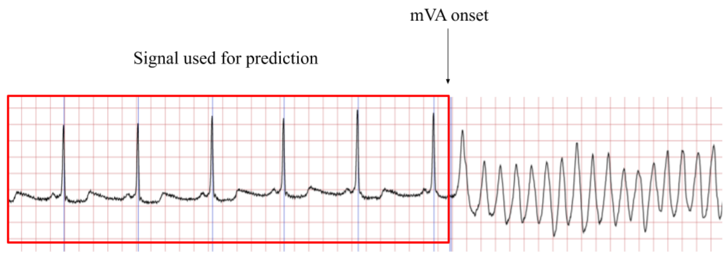

Fig. 1 - ECG signal before mVA onset (shown in red box) is extracted from each mVA record for mVA prediction.

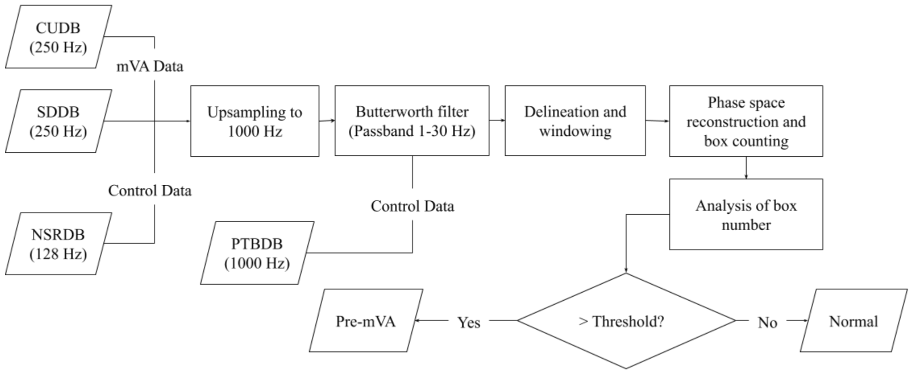

Fig. 2 - Workflow for prediction of malignant ventricular arrhythmia in this work.

To construct a phase portrait of ECG, a window of 10 successive RR segments was chosen. ECG signals in each window were normalised and a 20-ms delay was applied to obtain a total of 10 trajectories in the two-dimensional phase portraits. The phase portrait was exported as a high-resolution grey-scale image of pixel size 1024x1024 as shown in Fig. 3. Once the phase portrait was constructed, box counting was employed whereby the pixels through which at least one trajectory had passed were considered as boxes and the others were not. A sliding window of 10 beats was moved consecutively by one beat throughout the whole record (Fig. 4) and this resulted in a series of box count for each record (Fig. 5).

Parametric statistical analysis was carried out on each window of 25 successive box count visited by trajectories and *CV* or κ of the box count were estimated. A sliding window of 25 box count was moved consecutively by one box count throughout the whole record (Fig. 5) and this resulted in a series of *CV* or κ for each record. The value located nearest to the upper left corner of Receiver Operating Characteristics (ROC) curve was chosen as the optimal threshold of *CV* or κ because it gave high and balanced sensitivity and specificity. The whole series of *CV* or κ of box count for each record was passed through the optimal threshold. Once the threshold was exceeded, the record signal was categorised as ‘going-to-mVA’ signal, otherwise the signal was deemed as ‘normal’.

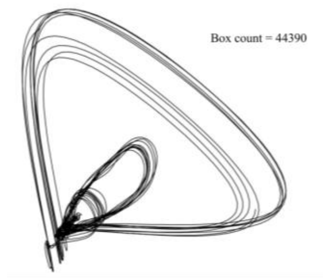

Fig. 3 - Each window of 10 RR segments results in one phase portrait and one box count.

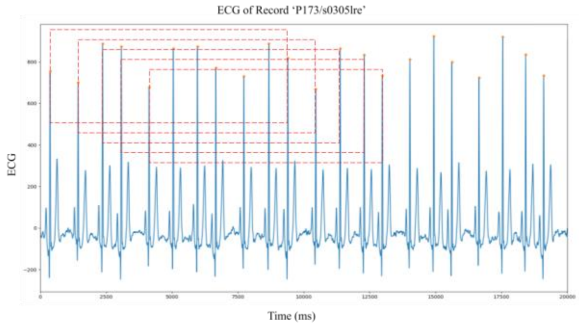

Fig. 4 - Sliding windows of 10 RR segments.

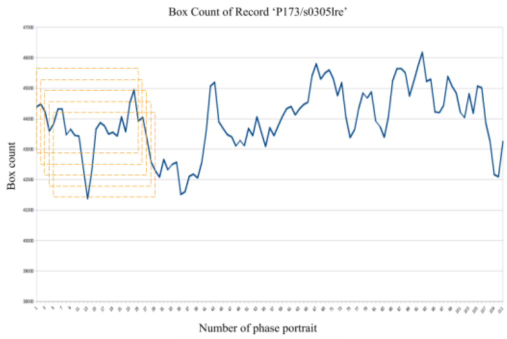

Fig. 5 - Sliding windows of 25 phase portraits (box count) for the whole record 'P173/s0305l.

2.3 Experiment

Three experiments were carried out to study the effect of different windowing methods, data representation methods of phase portrait and testing databases on the prediction performance of PSR box counting. The same workflow in Fig. 2 was implemented with slight variation in the PSR box counting method as well as the database utilised for analysis. Each experiment is briefly explained below.

The first experiment investigated the effect of different windowing methods on prediction performance. For phase space reconstruction, a fixed duration of a signal, for example, eight-second signal in [18], was usually employed to construct the phase portraits. Considering that fixed duration of signal may result in half a beat or some extra parts of beat that may break the trajectories periodicity, phase space reconstruction using fixed number of beats was proposed in [14] . The authors used a signal spanning over 10 heartbeats. In this experiment, windowing of signal using RR segments was studied and compared with that of using heartbeats and fixed duration. RR segment was chosen as the new basis for construction of phase portraits instead of beat because it required detection of only R peaks instead of the onset of P wave and offset of T wave. It was less prone to signal noise and misdetection. Since time window was the most used windowing method, it was implemented as a baseline comparison to the proposed method. Window length of 10 seconds was chosen, and a sliding window of 10 seconds was moved in steps of 1 second throughout the whole record. The three different types of windowing method based on time, heartbeat and RR segment are illustrated and juxtaposed in Fig. 6. To benchmark the performance against work in [14], CUDB and PTBDB were used in this investigation.

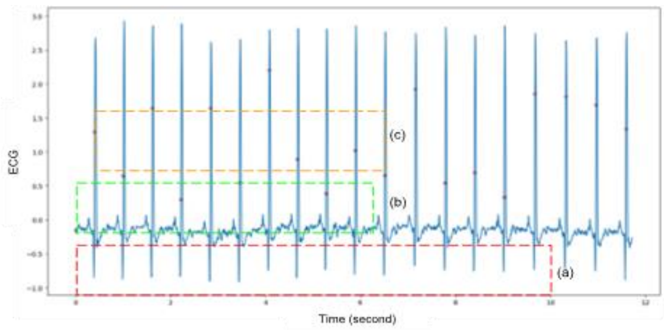

Fig. 6 - Windowing methods based on (a) time (signal spanning over 10 seconds), (b) heartbeat (signal spanning over 10 heartbeats) and (c) RR segment (signal spanning over 10 RR segments).

The second experiment examined different data representation methods of phase portrait. Linking and unlinking phase portrait were two different data representation of phase portrait. Linking phase portrait was constructed by connecting all the ECG data points on the portrait by curves (using *matplotlib.pyplot.plot* function) while unlinking phase portrait was constructed using only the positions of each discrete ECG data points without connecting them. Fig. 7 illustrates the examples of linking and unlinking phase portraits. Amann et al. [18] suggested that connected data points in phase portrait, which is linking phase portrait, might decrease the quality of box counting. Besides, linking and unlinking phase portraits were used in different works, for example, linking phase portraits in [19], [23] and unlinking phase portraits in [18], [24]. Their effect on the performance of box counting had not been studied and hence was investigated in this experiment. Using window of RR segments, both linking and unlinking phase portraits were constructed. Their performances were then evaluated using data from CUDB and PTBDB, as in the first experiment. Most prediction works were using NSRDB instead of PTBDB (Table 1) for the control signal. Hence, to further investigate the performance of linking and unlinking phase portrait, data analysis was also performed on CUDB and NSRDB.

(a) (b)

Fig. 7 - (a) Linking phase portrait. (b) Unlinking phase portrait.

The third experiment was about investigation on different testing databases. Some previous works of mVA prediction obtained arrhythmic signals from SDDB instead of CUDB (Table 1) and hence SDDB was included in this experiment. In our previous experiment, control signals were obtained from either PTBDB or NSRDB. They were both included in this experiment. The PSR box counting was applied on signals from NSRDB, PTBDB, CUDB and SDDB to examine its performance and versatility over the different databases. In this experiment, the work of [13] was selected for benchmark because it reported analysis results on multiple databases while other works only compared signals from one arrhythmic database and one control database, as summarised in Table 1.

Table 1 - Previous works acquired arrhythmic and control signals from different databases.

Signal Type	Database	Previous Work
Arrhythmic	CUDB	[13], [14], [25]
	SDDB	[6], [8], [12], [26], [27]
Control	PTBDB	[14]
	NSRDB	[6], [8], [12], [26], [27]
	Others	[11], [13], [28]

3. Result

3.1 Investigation Windowing Method: Windows of Fixed Duration, RR segments and Heartbeats

All the three windowing methods were tested using linking phase portraits on the 32 CUDB records and 32 PTBDB records. Table 2 presents the prediction performance achieved by PSR box counting using the different windowing methods. The highest prediction performance was achieved through our method of using RR segment as the basis of PSR window. Firstly, taking *CV* of box count as the sole feature for mVA prediction, windowing method using RR segment achieved higher accuracy and sensitivity than that of using fixed duration and heartbeat. Besides, compared to [14] which predicted mVA events using two features (*CV* and *kurtosis* of box count), the equivalent accuracy, sensitivity and specificity were achieved by our RR-segment-windowing method which utilised only a single feature (*CV* of box count) for prediction. The average prediction time achieved by *CV* feature in our study was 16 seconds earlier than that of combination of *CV* and *kurtosis* features in the previous research.

Table 2 - Investigating the effect of different windowing methods on the prediction performance using PSR box counting.

Windowing Method	**Heartbeat window** [14]			**Fixed Duration Window**		**RR Segment Window**	
Box Count Feature	*CV*	*Kurtosis*	*CV* and *kurtosis*	*CV*	*Kurtosis*	*CV*	*Kurtosis*
Accuracy, %	96.88	95.31	98.44	92.19	90.63	98.44	92.19
Sensitivity, %	93.75	90.63	96.88	87.5	81.25	100	87.5
Specificity, %	100	100	100	96.88	100	96.88	96.88
Prediction Time	-	-	4 min 31 sec (±2 min 30 sec)	3 min 56 sec (±3 min 1 sec)	3 min 8 sec (±2 min 8 sec)	4 min 47 sec (±2 min 8 sec)	3 min 12 sec (±2 min 34 sec)

3.2 Investigation on Data Representation Method of Phase Portrait: Linking and Unlinking Phase Portrait

Firstly, control signals and pre-mVA signals were obtained from PTBDB and CUDB respectively. Using *CV* threshold of 0.104 and 0.092, accuracy, sensitivity and specificity are calculated and shown in the left two columns of Table 3. The average prediction time achieved by linking phase portrait was nine seconds earlier than that of using unlinking phase portraits while their accuracy, sensitivity and specificity were identical. The only false positive case for linking phase portrait happened in ‘P150/s0287lre’, a control record, due to a larger drop of box count resulted from the presence of ectopic beats.

Table 3 - Performance comparison of *CV* feature extracted from PSR box counting using linking and unlinking phase portraits on ECG data from CUDB and PTBDB (left) or NSRDB (right).

Windowing Method	RR Segment window			
Feature	*CV* of box count			
Data Representation Method	Linking phase portrait	Unlinking phase portrait	Linking phase portrait	Unlinking phase portrait
Database (Number of Records)	CUDB (32), PTBDB (32)		CUDB (32), NSRDB (18)	
Accuracy, %	98.44	98.44	92	68
Sensitivity, %	100	96.88	87.5	78.13
Specificity, %	96.88	100	100	50
Prediction Time	4 min 47 sec (±2 min 8 sec)	4 min 38 sec (±2 min 18 sec)	3 min 24 sec (±2 min 34 sec)	3 min 28 sec (±2 min 42 sec)

For further investigation, control signals and pre-mVA signals were obtained from NSRDB and CUDB respectively. On the right two columns of Table 3, the accuracy, sensitivity and specificity were obtained using 0.14 and 0.167 as the *CV* threshold for linking and unlinking phase portrait respectively. Both data representation methods showed performance decline and it could be attributed to the different database being used for control signal acquisition, which was a non-noisy database (PTBDB) in previous testing and a relatively noisier database (NSRDB) in current testing. Smaller amplitude variation of box count due to the signal noises in NSRDB was observed in linking phase portrait method and its prediction performance was 33% higher than that of using unlinking portraits under this experimental setup. Linking phase portrait demonstrated more consistent performance over both noisy and non-noisy database.

Using *kurtosis* threshold of 7.6, 6.5, 7.6 and 9.54, accuracy, sensitivity and specificity are calculated and shown in Table 4. Linking phase portrait yielded higher performance than unlinking phase portrait regardless of the database used for control signal acquisition. Furthermore, similar performance decline was observed during evaluation of *kurtosis* feature using NSRDB instead of PTBDB. The accuracy drops for linking phase portrait (15%) was lower compared to unlinking phase portrait (20%) and it confirmed the higher noise resistance of linking phase portrait.

Table 4 - Performance comparison of *kurtosis* feature extracted from PSR box counting using linking and unlinking phase portraits on ECG data from CUDB and PTBDB (left) or NSRDB (right).

Windowing Method	RR Segment window			
Feature	*Kurtosis* of box count			
Data Representation Method	Linking phase portrait	Unlinking phase portrait	Linking phase portrait	Unlinking phase portrait
Database (Number of Records)	CUDB (32), PTBDB (32)		CUDB (32), NSRDB (18)	
Accuracy, %	92.19	84.38	78	68
Sensitivity, %	87.5	81.25	87.5	62.5
Specificity, %	96.88	87.5	61.11	77.78
Prediction Time	3 min 12 sec (±2 min 34 sec)	3 min 23 sec (±2 min 56 sec)	3 min 12 sec (±2 min 34 sec)	1 min 37 sec (±3 min 12 sec)

3.3 Investigation on Testing Database: CUDB, PTBDB and NSRDB

Based on the results of experiment 1 and 2 (Section 3.1 and 3.2), we selected windows of RR segments and linking phase portrait for PSR implementation in this experiment. This improved PSR method was evaluated using signals from PTBDB, NSRDB, CUDB and SDDB. We selected *CV* of box count as the sole feature due to its higher prediction performance. The same threshold obtained from the experiment using NSRDB and CUDB (0.14) was used to obtain the related performance metrics in Table 5. *CV* achieved high sensitivity (87.5% on CUDB, 90% on SDDB) and specificity (100% on both PTBDB and NSRDB) across the four different databases including the signals from SDDB and PTBDB which are excluded from the threshold derivation and selection.

Although [13] reported a slightly higher sensitivity, only 18 CUDB records were selected without stating the reasons for inclusion or exclusion, nor specifying the records used for analysis. In contrast, our study clearly specified the records used for analysis and a more balanced data sets were used, in which 51% were mVA records and 49% were control records. The performance was comparable to the previous research work [13] despite the inclusion of more mVA and control records in our analysis. Besides, our modified algorithm performance using *CV* as single feature attained similar performance as [14] that required two features, as shown in Table 2. Table 5 also demonstrates that our modified method is comparable to [29] which employed four nonlinear ECG features and machine learning technique on the same 20 SDDB and 18 NSRDB record signals.

Table 5 - Prediction performance of *CV* feature on ECG data from (a) multiple databases and (b) from SDDB and NSRDB.

Study	(a) Our Study	(a) [13]	(b) Our Study	(b) [29]
Method	Modified PSR method with maximum thresholding	Complexity analysis of T wave with maximum thresholding	Modified PSR method with maximum thresholding	ECG nonlinear method with support vector machine
Feature	Box count *CV*	T wave approximate entropy	Box count *CV*	Hjorth mobility, complexity, wavelet band energy, fuzzy entropy
Database (Records)	CUDB (32), SDDB (20), PTBDB (32), NSRDB (18)	CUDB (18), NSRDB+CINC Challenge database (40)	SDDB (20), NSRDB (18)	
Accuracy, %	94.12	93.10	94.7	94.7
Sensitivity, %	88.46	88.89	90	95
Specificity, %	100	95	100	94.4
Prediction Time	4 min 11 sec (±3 min 12 sec)	-	5 min 26 sec (±3 min 46 sec)	3 min

4. Discussion

Our result confirms that *CV* of box count of phase portrait is potentially one of the useful predictors for imminent mVA and the result is supported by [14]. *CV* describes the variation of box count relative to the mean in each window. Higher *CV* indicates higher complexity of signal and its underlying desyncronisation. This relative measure is particularly useful to investigate ECG data which differs in amplitude and morphology for each person. The versatility of this method is demonstrated by testing against multiple databases. However, the reduced performance on NSRDB shows that more consideration about noises, ectopic beats and so on need to be taken so that *CV* can be used in the practical situation of mVA prediction.

On the other hand, our result demonstrates the limited utility of *kurtosis* because it achieves lower prediction performance and requires higher computational effort. *Kurtosis* measures the individual deviation from the mean which are then raised to the power of four. Hence, it is heavily affected by the outliers of box count data. Signal noises may cause more, or more extreme outliers and hence high *kurtosis* of box count does not necessarily imply the signal desynchronisation for imminent mVA but a false alarm due to signal noises. More than 15% drop of accuracy during evaluation of *kurtosis* using NSRDB exhibits the low noise resistance capability of *kurtosis*. A more advanced signal filtering technique is required to make *kurtosis* a useful predictor.

In our work, ten RR segments are used for the construction of phase portrait in PSR because only detection of R peaks instead of heartbeat boundaries are required. It could be done reliably using well-known delineation algorithm [21] and have higher reliability in noisy data. Our work produces a better overall prediction performance compared to the windowing methods based on time and heartbeat in the previous work while reducing the complexities of computation for delineation and higher order statistics (*kurtosis*) compared to heartbeat-windowing method. The improved result could be attributed to more accurate segmentation of windows and hence more accurate phase space representation based on RR segment. Owing to RR segment's high noise resistance ability and low computational efforts, it would be interesting to investigate it as a new windowing method for extraction of other non-morphological features.

Based on our experimental results, for box counting of PSR diagrams, linking phase portraits are more resistant to signal noises. This is probably because linking phase portrait shows the underlying dynamics of data using trajectories instead of only the random points. It smoothens out the time series data and minimizes the consequence of small-amplitude noises, hence more resistant to noise. However, linking phase portraits are more vulnerable to the presence of ectopic beats which might also happen in normal rhythm. When ectopic beats happened, the box count and the *CV* increased much significantly in linking phase portrait method, raising the chances of false positive. Detection of ectopic beats followed by rectification or extended analysis on their characteristics could possibly increase the method’s performance as well as versatility. Conversely, unlinking phase portrait is more sensitive to signal noises. Signal noises caused larger amplitude variation of box count in unlinking phase portrait and resulted in higher coefficient of variation which implied higher complexity of signal. This increased complexity of signal might not be due to the physiological changes leading to imminent mVA but because of the electromyographic noises in signal. The signal noises increased the chances of false alarm and hence decreased the performance of unlinking phase portrait on a noisy database. Unlinking phase portrait could possibly achieve higher performance by incorporating more advanced signal preprocessing method for filtering or transformation.

Furthermore, the findings of the current study prove the importance of testing the prediction algorithm against more databases to ensure the general performance. It is obviously noticeable from the significant drop in performance of unlinking phase portraits when testing against NSRDB instead of PTBDB. It is due to the high variability of different subjects capturing their ECG signal at different conditions and hence high variance in the ECG data [30]. However, the use of different databases might reduce the comparability among the various prediction algorithms in different studies. Hence, we suggest while testing algorithm against multiple databases, the individual performance of an algorithm on each database could be reported (as in our work, sensitivity and specificity over each database were reported) to make it comparable to other studies wherever possible and to expose any issues on performance consistency of the algorithm.

5. Conclusion

This study was designed to investigate the feasibility of box counting technique of PSR. The analysis revealed that high prediction accuracy of 94.12%, sensitivity of 88.46% and specificity of 100% were achieved using coefficient of variation of box count derived from phase portraits constructed by windows of RR segments and represented by linked data and trajectories. The predictive power and versatility of this technique were corroborated by testing against multiple databases which included signal noises and ectopic beats. This improved technique is envisaged to be incorporated in future implementation of mVA prediction to enable timely diagnosis while different parameters such as time delay and window length could be tested for optimal performance.

Acknowledgement

This research is supported by the Collaborative Research in Engineering, Science and Technology Center (CREST) R&D grant T20C3-14 (4B244), FRGS grant 4F900 and University Research Grant 04G42 and 16H47.

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