

Segmenting Sound Waves to Support Phonocardiogram Analysis:

The PCGseg Approach

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Presentation Overview

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Pattern Mining in Phonocardiograms

Prediction of heart conditions using time series analysis.







Motivation

- The Stethoscope is a well established acoustic medical device for auscultation (listening to the internal sounds of an animal or human body).
- Issue with traditional stethoscopes is that the sound level is extremely low.
- Electronic Stethoscopes digitise the sound signals (for amplification purposes) and store the digitised data as a phonocardiogram (PCG); essentially a time series.
 This in turn provides an opportunity for machine learning to be applied to these time series to generate classifiers to support automated analysis of the sound signals; for example to identify heart conditions.



Phonocardiogram

A phonocardiogram is a plot of a high-fidelity recording of the sounds and murmurs made by the heart.



Time

Challenge

- Average number of points within a single PCG (time series) is over 355,000, thus processing a reasonably sized collection of PCG so as to build a classification model of some kind is not a viable option.
- One solution is to use some kind of random sampling to identify motifs (for example using the MK algorithm) within the time series that serve to discriminate between classes and use these to build a classifier; however, there is still a substantial computational overhead.
- Proposed solution is to segment the data and than recast into a collection of segment identifiers so as to make the problem more tractable.

Objectives

- To represent PCG point series in terms of their constituent shapes and sub-shapes (in a two-level hierarchy).
- The conjectured advantages are that:
 - The main information could be preserved.
 - A more succinct segmentation would be produced.
 - Early abandonment could be adopted.

PGCseg

- PGCseg is a bespoke segmentation mechanism specifically directed at the segmentation of PCGs.
- It subdivides a phonocardiogram (time series) into a sequences of shapes and sub-shapes.
- Four distinct shapes can be identified:
 - (i) slant, (ii) vertical, (iii) dome and (iv) flat.



Formalism

- A time series P comprises a set of n points, $P = \{p_1, p_2, \dots, p_n\}$.
- A segmneted point series S (segmneted uisng PGCseg) comprises a set of m segmnets, S = {S₁, S₂, ..., S_m} (m<n).</p>
- Each segment S_i comprises a pair $\langle S_p, S_c \rangle$:
 - S_p is a tuple < shape, type, length> where:
 - -shape in {slant, vertical, dome, flat},
 - -type in {up,down}, and
 - -length is the size of the shape in terms of number of points;
 - S_c is a set of sub-shapes $S_c = \{S_{c1}, S_{c2}, ...\}$.
- Each S_{ci} in S_c is a tuple <type, length, depth>, where:
 - -type in {up, down, flat}.
 - -length is the size of the shape in terms of number of points,
 - -depth is the height of the shape in terms of amplitude units.

Segments and Sub-Segments

Two-level hierarchy



Motif Detection

Once the time series have been segmented machine learning can be applied.

- Approach taken was to identify motifs within the time series and then use these in the context of a 1NN classifier.
- Motifs were identified using the MK algorithm.

MK Algorithm [Mueen, Keogh, et al., SIAM 2009]

Parameters:

- w a window of size (measured in terms of a number of points),
- **r** a reference value and
- k the number of motifs to be selected.

For each time series:

- 1. Select **r** random motifs of length **w**.
- 2. For each motif determine a similarity score with respect to all other motifs of length w in the time series.
- 3. Retain the to k motifs with the best similarity score.

(Euclidean Distance use as the similarity measurement)

1NN Similarity

To measure how well two motifs match five criteria were considered in turn so that an early abandonment process could be adopted.

Number of (parent) segmentsSegment shapes and typesNumber of (children) sub-segmentsSub-segment typesAverage sub-segment lengths and depths:
$$\sqrt{\sum_{i=1}^{j} (length_{X_{C_i}} - length_{Y_{C_i}})^2} + \sqrt{\sum_{i=1}^{j} (depth_{X_{C_i}} - depth_{Y_{C_i}})^2}}{j}$$

Evaluation Framework

- Objectives: To examine the operation of the proposed segmentation based 1NN with that of a bench mark MK based 1NN in terms of classification accuracy and runtime.
- Test data: A set of canine Mitral Valve disease PCGs collected by staff at the University of Liverpool Small Animal Teaching Hospital; 72 time series distributed over a set of four classes: {B₁, B₂, C, Control}.
- Metrics: Mean Accuracy, Precision, Recall and F-score and run time (hh:mm) calculated using 10-fold cross-validation.

Accuracy



Runtime (hours)

	Without PCGseg	PCGseg
Average (hours per experiment)	90	14
Total (hours for 9 experiments)	810	126

A reduction in runtime by a factor of **6.43**.

The average length of a single point series was reduced to 83,569 instead of 355,484, a reduction in size by a factor of 4.25.

Conclusions

- The PGCseg, coupled with MK and 1NN, approach has been presented.
- Evaluation conducted using a set of canine PCGs.
- Using the approach runtime was considerably reduced compared with not using segmentation data:
 - A reduction in <u>time</u> by a factor of **6.43**.
 - A reduction in <u>size</u> by a factor of **4.25**.
 - A best recorded <u>accuracy</u> of approximately **70%**.
- For future work: the intention is to improve on the presented approach by considering RNNs and/or frequently occurring motifs.

