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# A Neural Network and SOM Based Approach to Analyse Periodic Signals: Application to Oyster Heart-Rate Data

Andrew D. Hellicar, Ashfaqur Rahman, Daniel Smith, Greg Smith, John McCulloch
CSIRO Computational Informatics
Hobart, TAS 7000, Australia

***Abstract*— New sensor streams are being generated at a rapidly increasing rate. The sources of these streams are a diverse set of networked sensors, diverse both in sensing hardware and sensing modality. Machine learning algorithms are ideally placed to develop generalized methods for stream analysis. One exemplar problem is the detection and analysis of periodic structure within these streams. Our contribution is the proposal of a new machine learning framework that (i) classifies a signal as periodic or aperiodic, (ii) further analyses the signal to find periodic structure using a neural network, and (iii) groups the motifs in the periodic signals using a modified Self Organising Map algorithm. We also demonstrate the framework using data generated by an Oyster heart rate sensor. We find that the generalized approach our classifier improves the detection of signal periods by reducing the number of functions classified as periodic from 11% to 9%; however, most benefit occurs for period calculation with the number of erroneously calculated periods reducing from 14% to 4%.**

***Keywords—frequency estimation, machine learning***

## I. INTRODUCTION

Recently a novel Oyster Heart Rate sensor has been developed by the CSIRO and UTAS [1]. The data generated by this system presents a challenge familiar to many machine learning practitioners: with limited prior knowledge of the sensor signal, how to reduce the signal data dimensionality and provide meaningful information for subsequent processing by human experts. This challenge is highly relevant to the machine learning community as the number of networked devices is expected to reach 50 billion by 2020, increasingly devices generate new sensor streams and are configured in new sensing modalities [2].

The Oyster heart-rate signal exhibits a phenomenon common in time-series sensor data: the existence of periodic structure. Specifically we describe a machine learning framework capable of classifying a signal based on extracting the periodic structure from signals generated by sensors with no prior knowledge of the signal statistics. The algorithm conducts an initial coarse classification of the signal into periodic and aperiodic classes by combining a set of algorithms with a neural network based classifier. A further fine grained classification of periodic signals is conducted based on signal shape and similarity to other signals using a modified Self Organising Map (SOM) algorithm. The approach is capable of being deployed with multiple sensor types.

In addition to being a nice demonstration of techniques for signal analysis, our results on Oyster heartbeat signals are of importance because ultimately it enables the discovery of new relationships between the Oyster physiology and environment. These relationships will allow the Oyster farming process to be optimized to conditions resulting in increased productivity across the oyster harvesting industry.

This paper is structured as follows. Section II describes background material including the Oyster sensor system and implications for the signals coming from this sensor type, and previous work in period analysis and motif discovery. Section III presents our proposed framework; finally Sections IV and V present the results and conclusions respectively.

## II. BACKGROUND

### A. *Oyster sensor*

In [3] an optical-coupling based Oyster heart-rate sensor was introduced. The sensor uses red light (632nm) with a laser beam illuminating the Oyster heart and an optical fibre coupled photo detector to measure the optical signal reflected off the Oyster. A 1cm diameter hole was drilled into the Oyster shell to allow access to the heart. Results were presented demonstrating the ability of the sensor to measure periodic signals. The signals comprised of large peaks which is indicative of a specular reflection dominating the coupled signal at one point in the heart beat cycle. Measured heart rates were ~ 30bpm. However no details were given about automated methods for detecting the heart rate or variation in signal structure. This is likely due to lack of need as in this configuration the signals were very spiky and period extraction is a simple measurement between peaks. The sensor developed by CSIRO and UTAS consists of a 950nm reflective IR sensor placed in a small hole in the shell over the heart. With this arrangement the reflected signal exhibits more complex structure and a simplistic peak counting analysis is inadequate. Extracting information from this type of scenario has broader relevance and allows our period estimation technique is to be deployed across multiple sensor types.

*B. Periodic signal detection*

We begin by defining the type of signal we refer to within this paper, the time series sequence:

Definition 1: A sequence S = [S(1)….S(N)] is a time ordered sequence of real valued values.

Sequences have periodic structure if they consist of ordered sub-sequences, which are shorter and repeat across S. Formally we define a periodic sequence as:

Definition 2: A periodic sequence is composed of a series of temporally adjacent, non-overlapping sub-sequences (s) of interval length P , $s[i] = [S(i * P + 1) \dots . S((i + 1) * P)]$ , where i is the index of each sub-sequence. Each sub-sequence is equal to all other sub-sequences from the series, $s[i] = s[v], v \in S$ . In real applications, approximately periodic sequences are more common where the sub-sequences are not identical but just highly similar to one another.

Signals with approximately periodic structure are common in nature, for instance, water level patterns in water bodies will repeat with daily or bi-daily due to gravitational forces (the tide). Many physiological characteristics are periodic such as respiration, heart rate, brainwaves and physical oscillations produced as a consequence of motion. Previous heart beat analysis has involved human heart beat signals with regular structure [4].

Historically, an area that has spent significant effort upon fundamental period detection has been speech compression. The fundamental period, or as commonly known in the speech community, the pitch of voiced speech, is a perceptually important characteristic that can be coded efficiently. A problem common to these techniques is that these algorithms detect higher frequency harmonics of the actual period or sub harmonics. The problem becomes one of how to weight the different components. In [5] an approach is given for weighting these components based on a Hanning window. Here we describe six common techniques that have been utilized for speech pitch prediction. All the approaches described include a measure of periodicity which can be thresholded to separate the signals into periodic or aperiodic classes. In addition each approach estimates the signal period. Detailed explanations of the methods we utilize are presented in [6]. We briefly summary the key points of each method to aid in the understanding of the method's limitations and demonstrate the need for our machine learning solution. The six implemented to determine whether a signal S(t) t=1..N is periodic or not are:

*1) Autocorrelation function method (ACM)*

The autocorrelation function method [7] is

$$A(m) = \frac{1}{N} \sum_{t=0}^{N-1-m} S(t)S(t+m) \tag{1}$$

Where $m \in \{M\_min\ ..\ M\_max\}$. Typically $M\_min$ and $M\_max$ are selected based on prior knowledge of the signal statistics. Without prior knowledge we let M_max=N/2 and M_min be the first zero crossing of the autocorrelation (thus excluding the intitial peak of A(m) produced by coherence time of S(t). The sequence is classified as periodic if peak of A is larger than a threshold parameter and period P defined as value of m at peak.

*2) Modified autocorrelation function method (MACM)*

The modified autocorrelation function method involves a centre-clipping step before the autocorrelation approach is used. The centre clipping operation replaces S(t) in (1) with Sc(t):

$$S_c(t) = \begin{cases} S(t) - C, & S(t) > C \\ 0, & -C \le S(t) \le C \\ S(t) + C, & S(t) < -C \end{cases} \tag{2}$$

This technique emphasizes the peaks in the function in determining the periodicity.

Both these techniques weight shorter timescale interactions more highly as a result of the autocorrelation operation resulting in a linearly decreasing weight. They can accidently lock on to higher frequency component.

*3) Normalised Cross-correlation function method (NCFM)*

To avoid the problem of lower weighting of longer periods, the NCCF method normalizes each element in the auto-correlation such that NCFM(m) = A(m)/N(m) where A(m) is calculated as in (1) and N(m) is:

$$N(m) = \sum_{t=0}^{N-1-m} S^2(t) \cdot \sum_{t=0}^{N-1-m} S^2(t+m) \tag{3}$$

This technique introduces a weighting that corrects for the emphasis to shorter period signals. However any periodic sequences with small oscillation at a half frequency results in its autocorrelation being higher, and therefore erroneously detecting the lower frequency as it adds to the shorter period.

*4) Average magnitude difference function (AMDF)*

The AMDF is presented in [8]. Whereas the methods above use correlation to measure similarity the AMDF method minimizes the L1 norm of the shifted signal difference D:

$$D(m) = \frac{1}{N} \sum_{t=0}^{N-1-m} |S(t) - S(t+m)| \tag{4}$$

*5) Maximum likelihood method time domain. (MLTD)*

The maximum likelihood method simply selects a period P and sums the period sub-sequences in the sequence. The resulting summation is a function M(T) which is maximized at T=P.

$$M(T) = \frac{1}{b+1} \sum_{t=0}^{a-1} \left( \sum_{n=0}^{b} S(t+nP) \right)^2 + \frac{1}{b} \sum_{t=a}^{T} \left( \sum_{n=0}^{b-1} S(t+nP) \right)^2$$

where $a = mod(N, P)$ and $b = floor(N/P)$.

*6) Cepstrum method (CEPM)*

The Cepstrum method is described in [9]. The method involves taking the log of the sequences's spectrum magnitude before inverting to time domain and calculating the peak. The Cepstrum method is useful where the sequence is caused by a convolution process, which is the case for speech; however, less likely for heart deformation, possibly a muscle excitation convolved with muscle response.

$$C(m) = \frac{1}{N} |IFFT\{\log(|FFT\{S(n)\}|)\}| \quad (6)$$

*7) Neural Network approach*

Each of the described methods is suited to particular types of signals and have their own most likely failure modes. This algorithm diversity and the fact we have limited prior knowledge about the signal, motivates a machine learning approach. We apply all techniques and feed the periodicity and period values into a multi-layer perceptron (MLP) network (WEKA implementation [10]).

### C. Motif discovery

Heart rate motif discovery is a common approach in assessing heart beat structure in humans for illness identification. Standard approaches have used Dynamic timewarping type approachs based on shape functions for classifying signals [11]. SOM can be used to build clusters of similar motifs.

The self organizing map is a type of artificial neural network that is widely used to map high dimensional input into a lower dimension space (commonly 1 or 2 dimensions), which in turn can be used to visualize the similarity between high dimensional instances. The network (M) consists of a set of neurons that are represented by a map position and weight vector (w) with the same sized dimensions as the data instance. This network is trained to represent the underlying structure of a data set (D) through a competitive learning process that can be summarized as follows:

*Method 1 – SOM learning*

*1.1) Initialise each of the neuron weights* $w_z \in M$ where $z$ is its map position.
*1.2) For each data instance,* $d_i \in D$*:*
*a) Compute the Euclidean distance between* $d_i$ *and each* $w_z$.
*b) Select the neuron with* $w_z$ *that is a minimum distance to* $d_i$*. This neuron is known as the Best Matching Unit (BMU) in the network.*
*c) Update each* $w_z$ *in the network according to:*

$$w_{z,s+1} = w_{z,s} + u.v(z, z_{BMU}).(d_i - w_{z,s}) \quad (7)$$

where u is the learning rate, s is the index of the learning iteration and $v(z, z_{BMU})$ is a neighborhood function that influences the update of weights based upon their proximity to the BMU neuron. The weight update is based upon the distance between the map position of the current neuron (z) and the BMU neuron ($z_{BMU}$). A neuron at a smaller distance to the map position of the BMU will provide a larger update of its weight neuron. The influence of the neighborhood function will shrink as s increases. Hence, the similarity between neuron weights in particular regions of the map increase and begin to fit local regions of the data space.

## III. Proposed Framework for Signal Analysis

The proposed framework is shown in Fig. 1. Each of these steps are described in detail in the remainder of this section.

### A. Sequence formation

The entire signal is initially split into sequences of length N. N must be chosen to represent a time scale where the period (P) of the signal can be assumed to be approximately constant. Consequently, if the entire signal is approximately stationary (that is periodic is approximately constant), the signal does not need to be split into sequences. The periodicity of the real world signals, however, tends to change over time. In addition, N must be long enough to ensure that multiple periods of the signal are captured by the sequence (i.e. N>2*P) in order for the periodic structure to be estimated. After signal splitting the sequences are normalised to such that S(t) has zero DC component and $\sum_{t=0}^{N-1} S^2(t) = N$. We also generate a lower bound on P by calculating a time corresponding to the signals region of self coherence from the signal autocorrelation function. Specifically the lower bound is the time at which the autocorrelation first transitions from positive to negative and is related to the bandwidth of the signal.

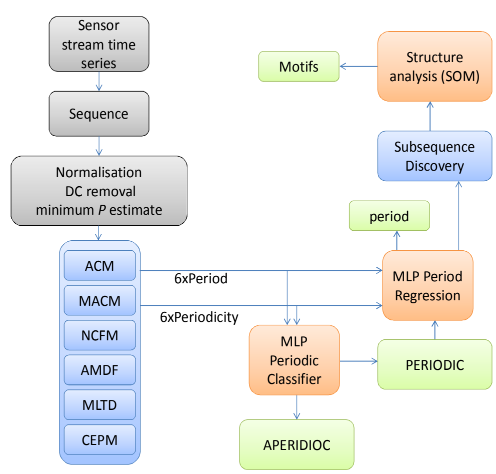



Fig. 1. Framework for classification of signal and determination of periodic structure.

The remaining processing steps (B and C) are performed upon each sequence of the signal independently.

*B. Periodic vs aperiodic classification of sequences*

Because of the limited information about the signal we implemented and tested each of the pitch detection techniques listed in Section IIB. To test the accuracy of the methods a number of the sequences were analysed manually to create a labeled dataset. Sequences were randomly selected and labeled as either periodic, aperiodic or uncertain until 100 sequences were in the periodic and aperiodic classes. The six periodicity values were fed to a multi-layer perceptron (MLP) that classifies the sequence as periodic or not. The MLP was trained using a 10 fold cross validation procedure on the data. The MLP (referred to as MLP1) was optimal with 2 hidden layers each containing 6 nodes with sigmoid activation functions and linear output node.

For periodic sequences a further analysis was conducted to determine the period. To analyse the accuracy of the period detection the period was manually calculated from the data on 144 sequences. These sequences were different from the aperiodic/periodic labeled set. The sequences were chosen because they spanned large regions of the signal maintaining a periodic state. The period was linearly interpolated between the labeled times. Because the failure mode of the methods are likely to lock onto multiples of the period of the form P/k or kP we define a method as being correct if it finds a period Pi such that 0.8 P < Pi <1.2 P. This also allows our manual period calculation and interpolation to include some error without effecting the estimation of the accuracy of the approaches. In addition to optimal selection of threshold values a second MLP regression (MLP2) was trained with the set of period and periodicity values as inputs to determine the signal period. The MLP was trained using a 10 fold cross-validation similar to the MLP periodic signal classifier. This MLP was optimal with a single hidden layer containing 6 nodes.

*C. Periodic structure estimation*

Given the estimated period (P), a single, best estimate of the periodic structure of the sequence is computed. The most representative period can be estimated by applying the cross correlation function to each sliding window of P samples in the sequence (used to represent each periodic sub-sequence candidate) with respect to the entire sequence:

$$A(p,m) = \frac{1}{N}\sum_{t=0}^{N} S(t+m)SW_P(t), \qquad p = 0 \dots N-P$$
$$SW_P(t) = [Z_1, \mathrm{S(p)}, \dots, \mathrm{S(p+P)}, Z_2] \qquad (8)$$

where $Z_1$ and $Z_2$ are vectors of zeros of length $L_1$ and $L_2$ such that $L_1 + L_2 + P = N$ and therefore $Z_1$ and $Z_2$ pad the window SW to ensure it is the same length as the sequence. The variable $m$ represents the sequence shift in the cross-correlation function and variable $p$ represents the start sample of the sliding window. The signal is selected as the time-shifted window $SW(t,p)$ (with zero padding removed) that possessed maximum energy in the function defined according to:

$$\arg\max_{\mathrm{p}}\ \mathrm{A(p)} = sum(\textstyle\sum_{m=P}^{i\cdot P} A(p,m)) \qquad (9)$$

where i is largest integer satisfying $\mathrm{i} \cdot \mathrm{P} < T$. The window that possessed maximum cross correlation energy at integer multiples of the estimated P was the optimal periodic sub-sequence of the sequence.

*D. Periodic Motif discovery*

In the final stage of the algorithm, the self organizing map is used to discover a set of periodic motifs. The data instances ( d ) of the SOM are the periodic signals that have been estimated from the sequences with (9).

*D1. Issues with the Self Organising Map*

There were two issues that needed to be addressed with using the conventional SOM (described in section IIC) before it could be applied to the motif discovery task. The first issue was that the number of samples belonging to each data instance varied due to differences in the periodicity of sub-sequences. The SOM requires that all data instances have a consistent dimensionality; with time series clustering, this equates to ensuring there is a consistent number of samples. Consequently, the set of periodic series were re-sampled to a consistent dimensionality (sample size), ensuring re-sampling did not extensively degrade the shape of signals in the process. The amplitude of each periodic signal was then normalized to values between 0 and 1.

The second issue was that there was no guarantee of consistency in the temporal ordering of different data instances. The correlation criteria in (9) identified the periodic signals with maximum correlation, but the starting points of the discovered sub-sequences are likely to be different, even when they have a similar shape. This is problematic when clustering the signals using the Euclidean distance. For instance, the distance between two identical periodic signals with different phase (different starting points) may be large, and hence, will update different BMU during the training of the SOM.

One simple approach was to take a reference point upon all of the data instances. The minimum value of each subsequence was selected as its start point and shifted before the SOM was applied. The result of such an approach, however, was found to be unreliable given the presence of noise. A second reliable but computationally intensive approach was to modify the SOM learning process, such that an optimal alignment was found between each motif and neuron weight prior to the update equation in (7). This optimal alignment was computed with the cross-correlation function between d and w. The modified temporally invariant SOM learning process can be defined as follows:

*Method 2 – temporally invariant SOM learning*

*2.1) Initialize each of the neuron weights* $w_z \in M$ where $z$ is its map position.
*2.2) For each of the periodic signals in the data set* $d_i \in D$:
*a) Compute the cross correlation between* $d_i$ *and each* $w_z$ *in the network:*

$$A(m, w_z) = \frac{1}{P}\sum_{t=0}^{P} w_z(t) d_i(t+m) \quad (10)$$

*where m are the time lags, m=0…P.*
*b) Select the* $w_z$ *with a maximum cross correlation* $A(m)_{max}$. *The neuron associated with* $A(m)_{max}$ *becomes known as the best matching unit (BMU).*
*c) Update signal* $d_i$ *by shifting it by* $m$ *samples. This corresponds to a time shift that produced a maximum value for* $\mathrm{A(m, w_{BMU})}$.
*d) Update each* $w_z$ *in the network according to:*

$$w_{z,s+1} = w_{z,s} + u.v(z, z_{BMU}, r).(d_i(t+m) - w_{z,s}) \quad (11)$$

where $u$ is the learning rate, $s$ is the index of the learning step and $v(z, z_{BMU}, r)$ is the neighborhood function comprised of the normal distribution $e^{-\frac{(z-z_{BMU})^2}{r^2}}$ where r is the radius distance, $z$ is the map position of the current neuron and $z_{BMU}$ is the map position of the BMU neuron. The cross correlation function of the temporally invariant SOM replaces the Euclidean distance of the SOM in (1.2a). Whilst the cross correlation was used to select the BMU of each data instance similarly to the Euclidean distance, in addition, it enabled each periodic signal to be optimally aligned to their BMU before update in (2.2d).

## IV. RESULTS

An oyster was instrumented with an IR sensor and placed in the intertidal zone in the Derwent River in Hobart, Australia. The sensor was connected to a custom made acquisition / telemetry control unit. The control unit was configured to acquire data from the IR sensor approximately every 7 minutes. Each acquisition consisted of 20 seconds of IR data sampled at 100Hz. Six weeks of this data is analyzed in this paper.

### *A. Periodic versus non-periodic classification*

The performance of the 6 algorithms is highlighted in Fig. 2. If the optimal threshold is selected for each algorithm the three best algorithms performed similarly with (MLTD) correctly classified 89% and ACM and MACM classifying 88% of the cases at optimal threshold value. The MLP1 classifier performed better at 91%.

The fraction of incorrectly and correctly calculated periods are shown in Fig. 3 for all possible threshold values in the six methods and the neural network classifier. Although the apparent performance of some of the algorithms is obviously bad it is naïve to dismiss these methods. Firstly performance is sensitive to the statistics of the analysed data set, and relative performance may change for other data sources. Secondly although some of the methods are regularly getting the period wrong, the error is often a consequence of the algorithms generating solutions at integer harmonics or sub-harmonics. For example when the AMDF period is plotted against ACM period, many low ACM periods correspond to larger periods calculated by AMDF (Fig. 4). The harmonic structure is evident with straight lines superimposed at 1x, 2x and 3x ACM period. Therefore information is contained in the output of the 'erroneous' methods. The MLP algorithm is able to learn this information and period estimation improves as a result. With 3.4% of results in error, MLP2 achieves 96.6% correct, whereas the best method (ACM) can only achieve 86% correct at the same error rate.

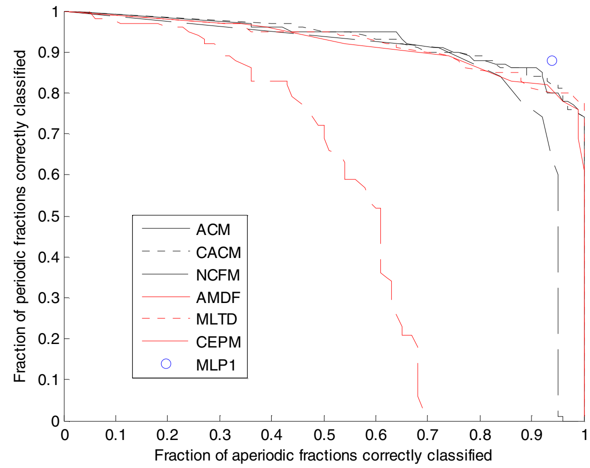



Fig. 2. Classifier performances as threshold values are varied.

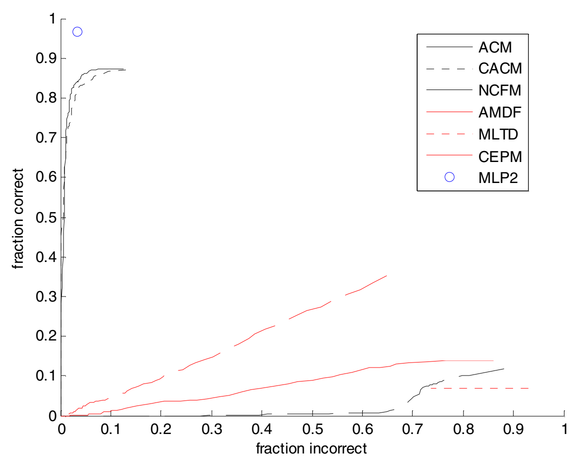



Fig. 3. Algorithm performance as threshold values are varied.

A set of 3793 heart beat sequences were classified as periodic and their fundamental period was estimated using the MLP approach described in section IIB. The optimal periodic signal of each sequence was then computed using (8). Each of the periods were resampled to a size of 40 and normalized between values of 0 and 1. The set of representative periods

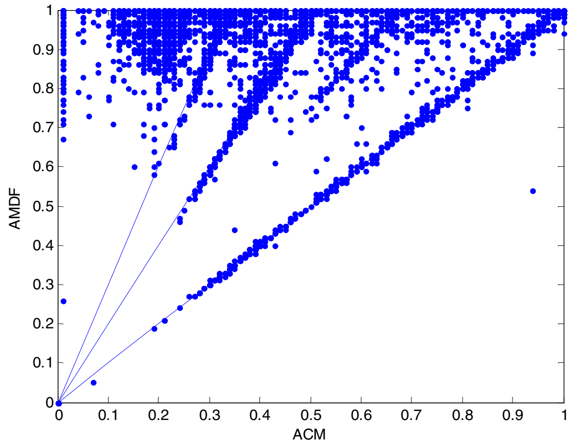
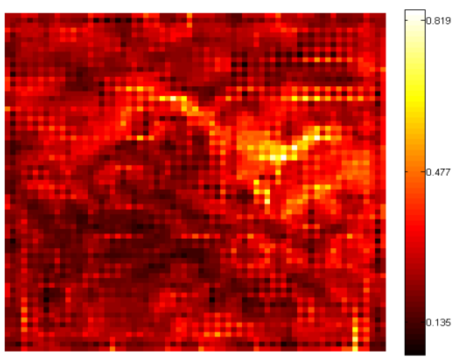
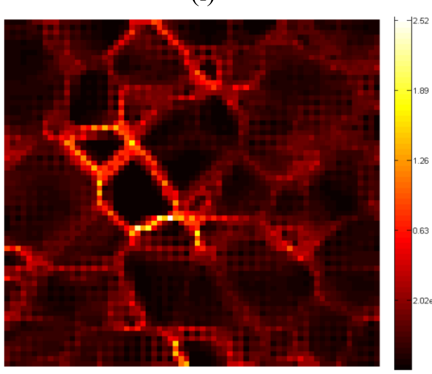



Fig. 4. Period calculated from AMDF plotted against periods estimated from ACM.

were clustered with both the SOM (Method 1) and temporally invariant SOM (Method 2). The U-matrix map of the original SOM and temporally invariant SOM are shown in Fig. 5. The U-matrix is used to visualize the data space by representing each neuron in the SOM as the Euclidean distance between its weight vector and set of adjacent neuron weight vectors. The temporally invariant SOM had far more localized clusters of low Euclidean distance compared to the original SOM that had broader regions with far more variance. These low distance clusters of neuron weights each represent a unique motif. Hence, only the temporally invariant SOM was used to




(i)




(ii)

Fig. 5. The U-matrix map of the (i) SOM and (ii) temporally invariant SOM learnt from 3793 heart beats. The map represents the Euclidean distance between the neuron weights and neighbouring neuron weights.

discover a set of motifs.

The k-means algorithm was applied to the codebook of 900 weight vectors learnt by the temporally invariant SOM. The k-means algorithm was required for motif discovery given the weight codebook of the SOM was highly redundant. The number of clusters used by the k-means algorithm was set to 15. This number of clusters was selected by identifying the number of low distance clusters in the SOM (Fig. 5(ii)). The weight vector that was the median distance to its corresponding cluster centroid (computed from k-means) became a discovered heart beat motif. The 15 discovered heart beat motifs are shown in Fig. 6.

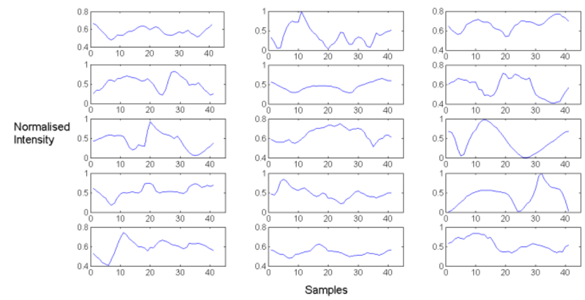



Fig. 6: The 15 heart beat motifs discovered after applying k-means to the weight codebook of the temporally invariant SOM.

The clusters labels are plotted on a time series in Fig. 7. This plot gives an indication of the long term temporal behavior of the oyster heart beat based on what type of motif it had at what time. This helps the oyster physiologists to identify events and how they relate to environmental variables or other parameters.

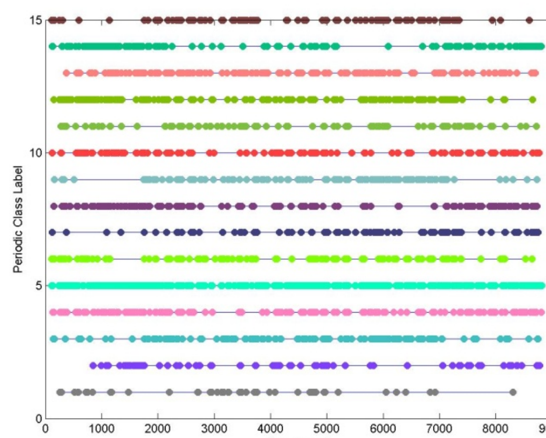



Fig. 7: Time ordered plot periodic sequences labels classified into 15 discovered oyster heart beat motifs shown in Fig. 6.

## V. Conclusion

Practical signals from sensor streams exhibit complex structure and no single approach is ideal. We have proposed and implemented a neural network approach and show greatly enhanced performance for the period estimation problem. We have also presented a modified SOM algorithm to cluster motifs that takes into consideration the signal alignment while computing distances. Although computationally more expensive than any single method, and requiring some initial human intervention in generating labeled sets, the advantage is the signals can be correctly classified as periodic/aperiodic ~91% of the time and period estimated accurately ~96.6% of the time. Future work will involve improving the aperiodic/periodic classifier by using a larger training set and testing the method on different input streams. We also aim to investigate automated ways to associate the oyster heart rate motifs to environmental variables and discoveries of events.

## ACKNOWLEDGMENT

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