Application of Wavelets and Kernel Methods to Detection and Extraction of Behaviours of Freshwater Mussels*

Piotr Przymus[1], Krzysztof Rykaczewski[1], and Ryszard Wiśniewski[2]

[1] Faculty of Mathematics and Computer Science,
Nicolaus Copernicus University, Toruń, Poland
[2] Laboratory of Applied Hydrobiology,
Nicolaus Copernicus University, Toruń, Poland

Abstract. Some species of mussels are well-known bioindicators and may be used to create a Biological Early Warning System. Such systems use long-term observations of mussels activity for monitoring purposes. Yet, many of these systems are based on statistical methods and do not use all the potential that stays behind the data derived from the observations. In the paper we propose an algorithm based on wavelets and kernel methods to detect behaviour events in the collected data. We present our algorithm together with a discussion on the influence of various parameters on the received results. The study describes obtaining and pre-processing raw data and a feature extraction algorithm. Other papers which applied mathematical apparatus to Biological Early Warning Systems used much simpler methods and their effectiveness was questionable. We verify the results using a system with prepared tags for specified events. This leads us to a classification of these events and creating a *Dreissena polymorpha* behaviour dictionary and a Biological Early Warning System. Results from preliminary experiments show, that such a formulation of the problem, allows extracting relevant information from a given signal and yields an effective solution of the considered problem.

Keywords: Automated biomonitoring, Biological Early Warning System, Wavelets, Time series, Zebra mussel (Dreissena polymorpha).

1 Introduction

Monitoring of water contamination is one of the most crucial aspects of environmental and health care. Many existing monitoring systems examine water only for a narrow range of substances and work without continuous control. For that reason, systems based on life organisms, i.e. *Biological Early Warning Systems* (BEWS), increasingly gain interest and popularity. Building BEWS is a complex

* This work was supported in part by the Marshall of Kuyavian-Pomeranian Voivodeship in Poland with the funds from European Social Fund (EFS) (a part of integrated operational program for regional development, activity 2.6) in the form of a grant for PhD students (Step in the future program, second edition).

T.-h. Kim et al. (Eds.): FGIT 2011, LNCS 7105, pp. 43–54, 2011.

task, which requires a choice of a relevant bioindicator for the monitored environment, preparation of an activity measuring system, that will provide data for further processing, developing analysis and characterisation methods.

As aquatic organisms are sensitive to the concentration changes of different life supporting substances or the presence of xenobiotic, stressing or toxic compounds in the water, they are eligible as bioindicators. Most frequently used as sensing elements are cladocerans [1, 2], amphipods [3], bivalves [4, 5, 6], aquatic insects (*Chironomidae*) larvae [7] and fish [8]. Especially mussels, like *Mytilus* or *Dreissena*, as sessile bivalves, are very suitable for long-term, *in situ* water quality monitoring.

There are several methods for measuring the response of mussels to stressing factors. In older systems it was measured as a frequency of shell closing-opening events, through gluing wires to both halves of the shell and connecting them through the interface to a computer [9, 10]. The number of closed mussels in a treated group, in comparison to control, was a measure of stress response. More recently, a wire was replaced by a magnetic coil (or Hall sensor), on one valve, and a magnet on the other [11]. The value of the amplified signal was proportional to the distance (gape) between the two valves. As a response to stress of a tested group, the average value of gape in comparison to control mussels was measured. Both systems have limitations in informative and interpretative value of generated data. Our observations of *Dreissena polymorpha* mussels behaviour showed, that the response to stressing factor is more complex. The sequence of elementary events, i.e. an extent of gape change value and time of the return to the initial gape value can form specific patterns for various natural or stress caused activity rhythms. The presence of such rhythms was confirmed in [12].

In this paper, we propose an algorithmic, fully automated analysis method for extraction of the behaviour of the zebra mussels (*Dreissena polymorpha*). Because the behaviour of the zebra mussels is recorded as long series of shell states, logged every second, we needed an efficient analytic tools [7, 13]. For this reason, we applied mathematical apparatus of wavelets and kernel methods.

Detection of signal changes using the methods for spectral decomposition of time series is especially interesting. Fourier Transform (FT) technique can be applied to analyse the frequency spectrum, but it does not provide any insight into when a frequency component is present. In other words, we gain no information about either the time at which peak occurs or its duration in time (i.e. *localization in time*). Because of the limitations of the FT technique, we recommend using the wavelet transforms for investigating the long-term records of sudden changes in animal behaviour. Moreover, this approach may be used to dissecting the impact of unexpected events such as disruption in electric circuits.

The paper is organised as follows. In Section 2 we focus on obtaining and pre-processing raw data. Section 3 is devoted to give necessary background of wavelet theory. In Section 4 we present our behaviour extraction algorithm, which effectiveness is evaluated in Section 5. Finally, in two last Sections 6 and 7, we point out used programming tools and conclude discussing the results.

2 Materials and Methods

Biological Signal. Signal is a record of activity of freshwater mussels. We measure the changes of the distance between the valves. For a sample signal acquired from zebra mussel see Figure 2 on page 50.

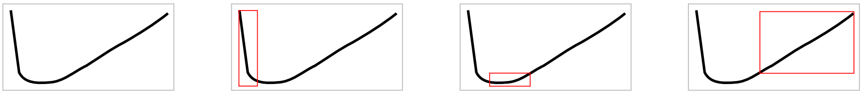
We want to extract single motions of mussels to classify them. It was proved in [12] that there are complex rhythms in the behaviour of *Dreissena polymorpha*. For example, the wanted pattern (shape of the graph of behaviour) may include the following phases: closing, resting and opening. These stages are presented in Figure 1 on page 46. Moreover, apart from the closing and opening phases, a vibration may occur. These are reactions to a stress or living activities. We search for time series fragments with following properties: at least closing and opening phases must appear, resting phase is optional; all phases may include perturbations. We analyse data with 16 minutes and 40 seconds (1000 seconds) periods of activity which from now on will be called *fragments*.

Measuring System. In our system, there are 8 mussels, which are located in a flow-through aquarium. They are attached to the ground, which does not affect their behaviour because of their sedentary nature.

We measure the changes of a magnetic field of a magnet placed on one side of the shell with a sensor placed on the other part of the shell. Data is collected every second from the sensors and transmitted to a database. The result sets showed, that the first prototype generates quite noisy data. Therefore, the measuring system should be improved in the future. The main difference between the old system and the new system will be based on used components type, their size and other resistance to interference from environment.

Obtaining and Pre-processing Raw Data. Denoising and data preparation steps consists of pre-processing filtering, removing white noise and averaging phase. A particularly important class of linear time-invariant systems are filters [14]. When the term frequency selective filter is used, it means that a system passes specific frequency components and totally rejects all others. This recommendation is common in particular for frequency selective filters like low-pass, band-pass and high-pass filters. A high-pass filter passes high frequencies well, but reduces the frequencies lower than the cut-off frequency. The real attenuation amount for each frequency differs from filter to filter. In our study, we used wavelet filter, which is high-pass filter and will be described later.

Analysis Method. Other papers investigated frequencies of closing-opening events [9, 10]. Previous results of observations conducted by the *Laboratory of Applied Hydrobiology at Nicolaus Copernicus University* reveal that one is able to extract motions as presented in Section 2 and, based on the activity record, is able to successfully assign water pollution to appropriate behaviour of mussel [9]. Stressful situation affects them, but it does not have to be a very violent reaction. For example, cyanotoxins and herbicides provide a recognisable, but not very intense, reaction. Therefore, we decided to analyse the normal activity



(a) Pattern (b) Opening (c) Resting (d) Closing

Fig. 1. Elementary phases of *Dreissena polymorpha* behaviour from time series point of view

and activity in a stressful situation to determine whether there is a difference and how it emerges.

One approach is to use statistical deviation. As abnormal we can take something that happens infrequently [8]. Not all incidents of behaviour, that do not conform to the norm, show an abnormality that we are looking for. We try to identify the *frame* (which will be defined in Section 4) in terms of shape, but not in terms of intensity or range of temporary phenomena.

In the future, we want to go even further and beyond the aforementioned situations to take an analysis of the captured events.

3 An Overview of the Wavelet Theory

The fundamental theory of wavelets was put forward by Haar in 1909 and then developed at the end of the 1960s. Now it has been extensively documented [15]. Wavelets have been very successful as an analytical tool to represent signals, in denoising, data compression and in time-scale analysis of time series, to mention a few of their applications. We refer inquisitive reader for more details concerning wavelet theory to [16].

Results obtained by this method are better than these obtained by Fourier analysis or other filter methods [15]. Because wavelet transforms can be exploited to analyse even non-stationary signals, they have been used in many medical applications and have been successful alternative methods to Fourier analysis.

Wavelets, in contrast to the Fourier Transform, are examples of *Multiscale Resolution Analysis*, which means that wavelet coefficients contain at once information about the frequency and the time domain. Thanks to this, they are particularly useful where the knowledge of these two characteristics of the signal is needed at the same time [16].

Continuous Case. Historically, wavelet analysis begins with *Continuous Wavelet* Transform (CWT). It provides a time-scale representation of a continuous function where the scale plays a role analogous to the one of the frequency in the analysis with the well-known Fourier Transform (FT). The main wavelet (the so-called *mother wavelet*) is a real valued function, that satisfies the following relations: $\int |\psi(t)|^2 dt = 1$ (quickly disappears), $\int \psi(t) dt = 0$ (oscillates). There are two main operations on wavelets: shift and rescaling. By applying them to the mother wavelet we obtain a whole family of wavelets: for $j, k \in \mathbb{Z}$ and a wavelet ψ, let $\psi_{j,k}$ stands for the wavelet with scale j and displacement k, i.e.

$$\psi_{j,k}(t) = 2^{j/2}\psi(2^j \cdot t + k). \tag{1}$$

Wavelet transform is a mapping which assigns to a 1-dimensional signal $f(t)$ a 2-dimensional array $c_{j,k}$ in the following way

$$f(t) = \sum_{j,k} c_{j,k}\psi_{j,k}(t). \tag{2}$$

At every step of analysis, we have a convolution (which is a filter) and rescaling (n and t become $2n$ and $2t$, respectively).

By introducing the so-called *scaling function* ϕ_k (for more details see [16]) one can represent a signal as

$$f(t) = \sum_k b_k\phi_k(t) + \sum_j \sum_k d_{j,k}\psi_{j,k}(t) \tag{3}$$

where $d_{j,k} = \langle g, \psi_{j,k}\rangle = \int f(t)\overline{\psi_{j,k}(t)}\, dt$. The first sum represents the *approximation* A_j of a signal f at the level j which is given by the scaling function. The second sum represents the *detail* D_j at the level j and is given by wavelets. The key idea of the multiresolution is a decomposition of the signal into different scales and its reconstruction from the sum [15], e.g. $D_1+D_2+D_3+D_4+D_5+A_5$.

Discrete Wavelet Transform. Discrete Wavelet Transform (DWT) is a discrete version of the CWT, analogously like Discrete Fourier Transform (DFT) is a discrete version of the FT. In the equation (2) the DWT is given by the set of coefficients $c_{j,k}$.

The basic tool of wavelet analysis is a multiscale decomposition of the signals, which is implemented using multi-band wavelet complementary filters (high-pass filters and low-pass filters). Calculation procedure leading to this decomposition is called *Mallat algorithm* [15]. This algorithm allows a fast wavelet decomposition and a reconstruction of a signal.

Wavelet decomposition may be seen as a continuous time wavelet decomposition sampled at different frequencies at every level of the analysis. A suitable way to find the best level for the hierarchy, depends on the signal type. In general, the level is selected depending on the desired low-pass cut-off frequency [7].

Analysis Using Wavelet Packet Transform: Tuning of the Various Levels. Discrete Wavelet Transform (DWT) is a particular case of *wavelet packet analysis* [16]. Moreover, implementation of wavelet packet analysis is done by dividing whole time-frequency into smaller pieces. The main reason for taking wavelet packet (WP) into consideration is to be able to analyse non-stationary signals and their behaviour.

Selection of Appropriate Wavelets for the Considered Problem. Several different families of wavelet functions have been defined [15]. Each of them is characterised by different properties, such as smoothness, compact support, and so on. In our case, the selection of appropriate wavelet is done by the algorithm.

4 Event Extraction Algorithm

Let us now present our algorithm, which captures the events. Then we justify its correctness. Having a filtered signal we are trying to cut it into elementary events and analyse them. The algorithm was created in a parametric form. There are following parameters: `name`, `level`, `local_error_frame_size`, `box_cleanup`, `box_threshold`. Below the meaning of these parameters is discussed.

Notation. We analyse signal which is assumed to be a time series $\{x_i = x(t_i)\}_{i \in J} \subset \mathbb{R}$, where $T = \{t_i\}_{i \in J}$ is a discrete set of times and $J \subset \mathbb{N}$ is finite set of indices.

Each subset $F \subset T$ having the property

$$\text{if} \quad t_i \in F, t_k \in F \text{ with } i < k, \quad \text{then} \quad \forall_{i<j<k}\, t_j \in F \tag{4}$$

is called *event*.

Given $F = \{t_k\}_{k=k_0}^{k_1}$ by *frame of an event* we understand the set

$$F \times \left[\min_{k \in \{k_0, \ldots, k_1\}} \{x(t_k)\}, \max_{k \in \{k_0, \ldots, k_1\}} \{x(t_k)\} \right]. \tag{5}$$

Further, by *behaviour extraction* we understand extraction of events with the desired properties as presented in Section 2.

Construction of the Filter. Firstly, we prepare the data: we unfold the data and remove noise by using a *wavelet filter*. A wavelet filter is a non-linear digital filtering technique, usually necessary to perform a high degree of noise reduction in a signal, before performing higher-level processing steps. This filter turns off a signal component at a certain level of wavelet analysis, i.e. it sets out $D_n = 0$ in the reconstruction step. In our case filter have two parameters: `filter_name` (specifies the name of used wavelet in this filter) and `filter_level` (specifies which component of the signal is turned off).

Local Error Estimator. In Figure 2, in addition to the high frequency components of the signal, we show a plot of a function, which is proportional to the absolute value of *the kernel weighted average* (*the Nadaraya-Watson kernel regression estimator*), in a neighbourhood of each point x_i. It is the convolution of Gaussian density function $\eta(t) = \frac{1}{\sqrt{2\pi}} e^{-t^2}$ and the signal x, which in the discrete case is given by

$$k_x(x_{i_0}) = [\eta * x](x_{i_0}) = \sum_{i \in J} \frac{e^{-\frac{(i_0 - i)^2}{\sigma}}}{\sqrt{2\pi}} \cdot x_i, \tag{6}$$

where $\sigma =$`local_error_frame_size`, $x_{i_0} \in x(T) := \{x_i\}_{i \in J}$. For more details and other kernels see [17]. At this stage, one could also calculate a common mean, i.e. $l(x_{i_0}) = \frac{1}{|J|} \sum_{i \in J} |x_{i_0} - x_i|$. This, however, does not take into account the local behaviour and gives, therefore, worse results.

Main Idea behind the Algorithm. The algorithm, which will be presented below, enables us to detect sudden jumps and sharp cusps in a time series by using a discrete wavelet transform. The idea is simple: a sudden jump of the time series affects the magnitudes of wavelet coefficients, so one can set a threshold level to find the point at which the jump occurs.

After decomposing a signal by using the wavelet packet with a wavelet function given by the parameter `name`, we search for interesting events. This computation can be described as follows. We consider detail of the given signal, which will be denoted by D, at the level which is given by the parameter `level`. According to our observations, in the component D there are a lot of information about the signal (sudden jumps, vibrations, fluctuations). Let us define x_+, x_- as positive and negative part of considered component, i.e.

$$x_+ = \left\{ \max(v, 0) \mid v \in \mathsf{D} \right\}, x_- = \left\{ \max(-v, 0) \mid v \in \mathsf{D} \right\}. \tag{7}$$

Plots of x_- and x_+ are shown in Figure 2 as continuous lines on the subfigures `start` and `end`. Let us define the *START* and *END* flags:

$$\mathsf{START} = \left\{ i \in J \mid (x_-[i-1] < k_{x_-}(x_i) \leqslant x_-[i]) \wedge (k_{x_-}(x_i) > w) \right\},$$
$$\mathsf{END} = \left\{ i \in J \mid (x_+[i-1] > k_{x_+}(x_i) \geqslant x_+[i]) \wedge (k_{x_-}(x_i) < w) \right\},$$

where k_{x_-} and k_{x_+} (dotted curves in Figure 2 on subfigures `start` and `end`) are kernel weighted averages for x_- and x_+ respectively (see 6) and $w =$ `box_threshold`.

The analysed component D may have a big disruption and this may result in frequent occurrence of events. It can be seen, that the parameter w provides a barrier beyond which the events occurred. Moreover, it prevents too frequent appearance of events. Here we find places where the signal is above or below the kernel weighted average at a given point, which is defined by formula (6). These points are suspected of being starts and ends of the frames.

Finding the best coverage by the frames using START and END flags can be done in the following way:

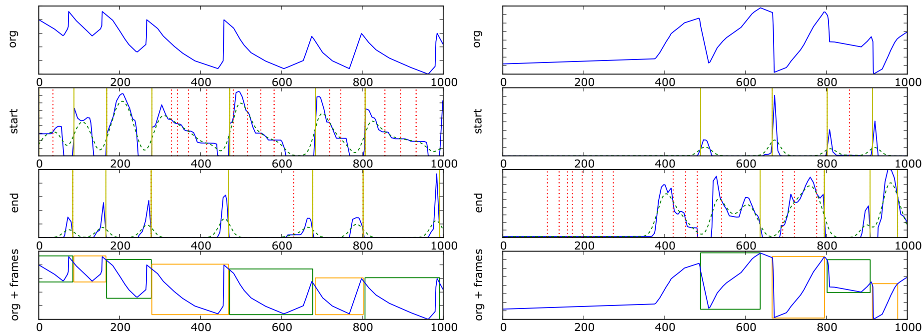
$$\mathcal{S} = \left\{ i \in \mathsf{START} \mid \exists_{k \in \mathsf{END}} \neg \exists_{j \in \mathsf{START}}\, k < j < i \right\},$$
$$\mathcal{E} = \left\{ i \in \mathsf{END} \mid \exists_{k \in \mathsf{START}} \neg \exists_{j \in \mathsf{END}}\, k > j > i \right\}.$$

The first element of START is supposed to be in the set $\mathcal{S}$. Further, one can show that the sets $\mathcal{S}$ and $\mathcal{E}$ sets contain the same number of elements. The sets $\mathcal{S}$ and $\mathcal{E}$ are declared to be the points at which opening and closing phases occurs, respectively.

In Figure 2, we can also see dotted vertical lines which represent points, that were suspected to be in the classes $\mathcal{S}$ and $\mathcal{E}$, but were omitted by this algorithm. Analysis of Figure 2 justifies the choice of these sets. Thus, we obtain the events

$$\left[\mathcal{S}(i_1), \mathcal{E}(i_1)\right], \left[\mathcal{S}(i_2), \mathcal{E}(i_2)\right], \ldots, \left[\mathcal{S}(i_q), \mathcal{E}(i_q)\right] \tag{8}$$

that have to be compared (which in general vary in length). Now we have to check if the selected events indeed generate good frames, i.e. if the height of a frame > `box_cleanup` × width of a frame. This algorithm is greedy. Therefore, we introduce parameter `box_cleanup`, which protects from taking into one event the whole fragment. Figure 2, shows the detected frames (last graph in each picture).



(a) (b)

Fig. 2. Frames extracted using our algorithm

5 Experiment Results

In this section, we will evaluate the effectiveness of the proposed algorithm, against the real data. All data were derived from experiments, in which impact of salt, herbicide and yeast on mussels was tested.

Data Specification. We used the data from 8 sensors with frequency of reading being 1 second. Each sensor recorded 11245 minutes of data which consist of reals from the interval $[0, 45]$. Sensor read error is assumed to be in the interval $[0, 3]$. Due to technical requirements the data set was split into time windows (fragments) of length 1000 seconds.

It is important to note that this data set is a subset from a bigger set of experiments, i.e. besides limiting data set, we only choose time fragments where height of the frame $>$ sensor read error.

Thus, in what follows, it is assumed, that everything what is below sensor read error is only a negligible perturbation. Considering this, we suggest using a more accurate sensor system. Some early experiments with better sensors (Hall sensors) show that our algorithm gains effectiveness.

The mussels were derived from the same colony. All biological experiments were conducted with at least 50% of mussels in control terms. There were also biological experiments conducted only in control conditions. Table 1 describes data set, obtained from this experiments.

Result Evaluation. The data set was independently analysed by two researchers who put markers in the areas of events described above. For comparing similarity between researchers and the algorithm we use *Tversky index* defined as follows:

$$S(X, Y) = \frac{\sum_{i,j} |X_i \cap Y_j|}{\sum_{i,j} (|X_i \cap Y_j| + \alpha |X_i - Y_j| + \beta |Y_i - X_j|)},$$

Table 1. Sum of read time for all mussels fulfilling conditions

Stressor	Herbicide	Yeast	Salt	Control
no oxygen	0	0	0	853 min
normal	853 min.	357 min.	986 min.	8193 min.

where $\alpha+\beta = 1$, X_i is i-th event and $|X_i|$ is its length. This asymmetric similarity measure, compares a *variant* to a *prototype*. We use values $\alpha = 0.75$ and $\beta = 0.25$.

With an algorithm constructed in such a way, we find the optimal parameter values using 30% of the data and event markers.

We measure similarity between markers provided by researchers and algorithm results. Moreover, we consider markers, of the researches, as a prototype and compare it using Tversky index with the algorithm results. Additionally, as Tversky index is asymmetrical, we also considered the case when algorithm is a prototype and researchers markers are a variant. See results in Table 2.

As a side note, it seems worth mentioning that the presented method is quite fast. For example, the data, obtained from 7375 minutes of the observations, is calculated in approximately 38.5 seconds (results were obtained on an Intel® Core™ 2 Quad CPU Q6600 2.40GHz).

Correctness of the Results. When choosing the best wavelet, which is then applied to the analysis of specified signal, shown in Figure 2, one should be guided by the well-known rule (see [15]), that the wavelets of "smooth" shape (e.g. `Morlet wavelet`) are characterised by better resolution in analysing signals in terms of spectrum, i.e. they are characterised by a better localization of frequency components on the frequency axis. Wavelets which are discontinuous or have slopes (e.g. `Haar wavelet`, `biorthogonal wavelet`), show better localization on the timeline. Therefore, the intuitions suggest that wavelets that are suitable for our purposes should have sharp cusps, which will caught a sudden jump in the signal. Indeed, at the stage of the automatic selection of the parameters, we obtained confirmation of our predictions.

Figure 2 clearly shows the characteristic signal in different frequency ranges, the amplitude and the location on the timeline. A notable feature is that the components with higher frequencies are concentrated in the relatively short length of time. The location agrees with the times of initiation or declines of movement of the mussel. This feature, which manifested distinct "peaks" in moments, corresponding to a behaviour phenomena are particularly evident at different levels of details. These facts give rise to the choice of beginnings and ends of single events in our system and explain our algorithm.

Optimization Results. During the optimization we obtained, the following parameters: `filter_name` = `db1`, `filter_level` = `aaad`, `name` = `rbior3.1`, `level` = `ddda`, `local_error_frame_size` = 450, `box_cleanup` = 0.12, `box_threshold` = 0.001. We see that the best results were obtained for the `rbio` wavelets, which have the above-mentioned properties (see [16]).

Table 2. Similarity between researches and algorithm clustered into cases of stressors

Experiment Description	User	User 1	User 2	Algorithm
Summary	User 1	x	0.712046377833	0.761884176385
	User 2	0.808793419224	x	0.715760702623
	Algorithm	0.648714212421	0.531441669327	x
Herbicide	User 1	x	0.73704199884	0.702517899468
	User 2	0.807069914053	x	0.716061338472
	Algorithm	0.666851522047	607025636399	x
Salt	User 1	x	0.685833427745	0.71389773682
	User 2	0.763362050728	x	0.629846521212
	Algorithm	0.677996432575	0.566973527048	x
Yeast	User 1	x	0.599296680011	0.647952077503
	User 2	0.766786953972	x	0.785170581729
	Algorithm	0.651532190762	0.623698430374	x
Control	User 1	x	0.712046377833	0.745311306628
	User 2	0.808793419224	x	0.766048200154
	Algorithm	0.705921742781	0.627110395079	x
Herbicide, no oxygen	User 1	x	0.73704199884	0.702517899468
	User 2	0.807069914053	x	0.716061338472
	Algorithm	0.666851522047	0.607025636399	x

6 Software Choices

Prototype implementation has been prepared in Python using `SciPy`, `NumPy`, `PyWavelets`, `MLPY`, `Matplotlib`, `flot` and `django`. `SciPy` is a Python library for mathematics, science and engineering. `NumPy` provides a library for convenient and fast N-dimensional array manipulation. Additionally, we used `PyWavelets`, a Discrete Wavelet Transform library to Python and `MLPY` – a machine learning library based on `NumPy` and GNU Scientific Library. The plots were prepared using `Matplotlib` and `flot`, the management layer and the experimental platform were prepared in `django`.

7 Conclusions and Future Work

Stressful situations can change the behaviour of mussels (both at the level of fundamental changes in the behaviour — anomalies can occur — and a rhythm disturbance of these behaviours). It can also cause an emergence of a new behaviour (e.g. testing the surrounding environment). The preliminary observations suggest, that there is a possibility of creating an alphabet of normal and abnormal behaviours, which will have to be extended depending on the stressful situations. Clustering of frames is possible and reasonable, but still some analysis details have to be modified to guarantee good results. It may be a good starting point for classification procedures, which will work very effectively.

Contributions of This Work

– We have developed a fast algorithm based on wavelets and kernel methods for the extraction of behaviours which in the future are going to be classified depending on the stressful situations.
– We have evaluated the effectiveness of the algorithm.
– We have developed a platform for an automatic behaviour detection and extraction.

Future Work. Proper functioning of this system requires gathering large quantities of mussels activities in natural conditions under high-stress factors and stressful conditions. Our further work will concentrate on the improvement of the clustering process, building of the alphabet and classifying the behaviours. We plan a set of experiments in laboratory and natural environment.

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