

# PHYTOPLANKTON DISCRIMINATION FROM FLUORESCENCE SPECTRA USING NEURAL NETWORKS

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## 1. Introduction

The analysis of phytoplankton species is really important in marine environment monitoring. Among the different techniques to measure seawater properties directly, fluorescence spectra analysis [1] has been used for this purpose. Several cultures representing different algae groups were grown under the same conditions and sampled every day. Excitation-Emission Matrices (EEM) were measured in order to obtain as much information as possible about cultures fluorescence spectra. This study evaluates the ability of the Self-Organizing Map (SOM) to achieve phytoplankton species discrimination from excitation spectra. The preliminary results are shown obtaining encouraging results.

### A. Fluorescence Spectroscopy

Fluorescence spectroscopy has become a powerful tool. The generation of Excitation-Emission Matrices (EEM) is widely used in marine environment to study the optical properties of the different organisms. Each sample is excited at different wavelengths and the emitted light is measured at several wavelengths. The production of these 3-D fluorescence landscapes (Figure 1) allows the visualization of a range of fluorophores in a given sample, in their relative positions in optical space. The technique is non-destructive and requires little or no sample preparation.

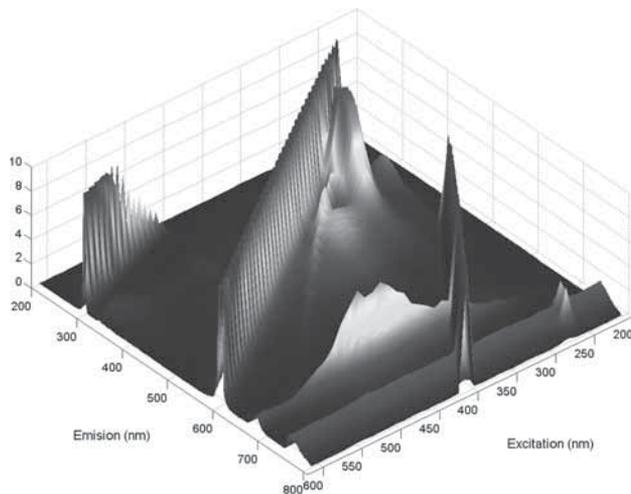


Figure 1. Excitation-Emission Matrix (EEM)

### B. Self-Organizing Map

Self-Organizing Map (SOM) [2] is a type of unsupervised ANN (Artificial Neural Network) particularly suitable pattern recognition and classification in high-dimensional feature spaces. The SOM method projects high-dimensional input data usually on a two dimensional map. A SOM consist of neurons organized on a regular grid, which are trained iteratively, in order to adapt to the input data in each step (Figure 2).

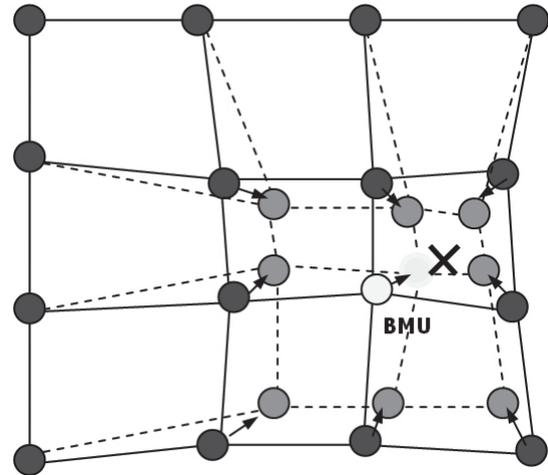


Figure 2. SOM network learning process

## 2. Results and Discussion

Seven different cultures representing the major algae divisions were selected (Table I) and grown under the same conditions. Every day, the EEM was generated for each of the seven cultures with an Aminco-Bowman Series 2 Spectrometer. The ranges of excitation and emission wavelengths of the samples were 200-600 and 200-800nm, respectively.

Species	Division	Abbreviation
Alexandrium minutum	Dinophyceae	Am
Thalassiosira weissflogii	Bacillariophyceae	Thwi
Dunaliella primolecta	Chlorophyceae	Duna
Isochrysis galbana	Prymnesiophyceae	Iso
Pleurochrysis elongata	Prymnesiophyceae	Pl
Synechococcus	Cyanophyceae	Syn
Ostreococcus	Prasinophyceae	Ost

Table I. Phytoplankton cultures under study.

As a first approximation, the excitation spectra at a 680nm have been taken into account. Then, the effect of Rayleigh and Raman scatters was evaluated, and its influence in the results was studied. This effect is practically negligible because the SOM method normalizes the value of each variable. However, the Rayleigh scatter was avoided averaging the previous and the following samples.

The training data set was generated containing five excitation spectra from each culture. These data were used by the SOM's neurons to learn, and the results are shown in Figure 3. As it can be seen, the clustering is successfully attained, i.e. the seven cultures can be easily distinguished.



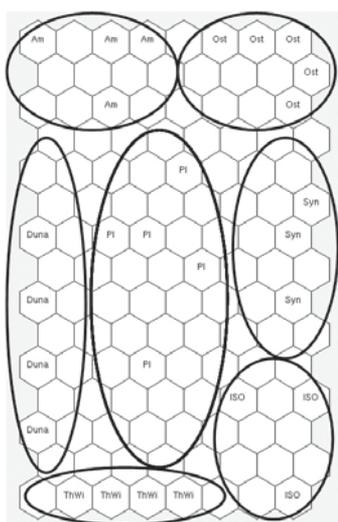


Figure 3. SOM label representation.

### 3. Conclusions

Excitation spectra from different cultures were measured, and were processed with the Self-Organizing Map. These preliminary results show the SOM methodology as a feasible way to achieve phytoplankton discrimination. Furthermore, they are encouraging enough in order to expand the current work into an automated system for phytoplankton's EEM classification.

### 4. Acknowledgements

The project VARITEC-SAMPLER (CTM2004-04442-C02-2/MAR) is funded from the Spanish Ministry of Education and Science.

### 5. References

- [1] M. Beutler, "Spectral fluorescence of chlorophyll and phycobilins as an in-situ tool of phytoplankton analysis –models, algorithms and instruments", PhD Thesis, University of Kiel , 2003.
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## NON WHITE GAUSSIAN NOISE REDUCTION ON MICROSTRUCTURE DATA USING WAVELET DENOISING

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### 1. Introduction

The characterization of the turbulent flow in the ocean dynamics has many implications in environmental modelling. The biological and physical processes characterization [1] [2] or the turbulent analyses of the energetic part of the vertical microstructure records [3] [4] are some of the fields on which we can focus the turbulent characterization.

A common procedure for detecting turbulent regions from CTD data is by computing the Thorpe displacements (dT) profiles [5]. The Turbulent patches are calculated from the density profiles  $\delta(z)$  and are identified as regions with non-null values of Thorpe displacements. The presence of noise is a critical problem when processing or analyzing the CTD data profiles. A method was proposed in [6] to improve patch detection at low-density gradients. The method, pointed out the influence of wavelet mother selection and the noise characterization on the final denoising results.

This article introduces a procedure to obtain the optimal wavelet filters selection to reduce noise effects. In the literature the studies based in wavelet denoising are focused on reduce the effects of white Gaussian noise. In turn, in this study, the signal representing the noise is synthetically created and modelled by both flicker and white Gaussian noise.

### 2. Noise Instrument Model

In this section we present the procedure considered to determine noise features in the Self Contained Autonomous Micro Profiler (SCAMP) measurements. This noise model will be used to optimize the Wavelet family to denoise the field profiles.

A set of laboratory test measurements were carried out for modelling the SCAMP noise. In these tests, the temperature was kept constant providing a reference to link the temperature fluctuations to the instrumental noise.

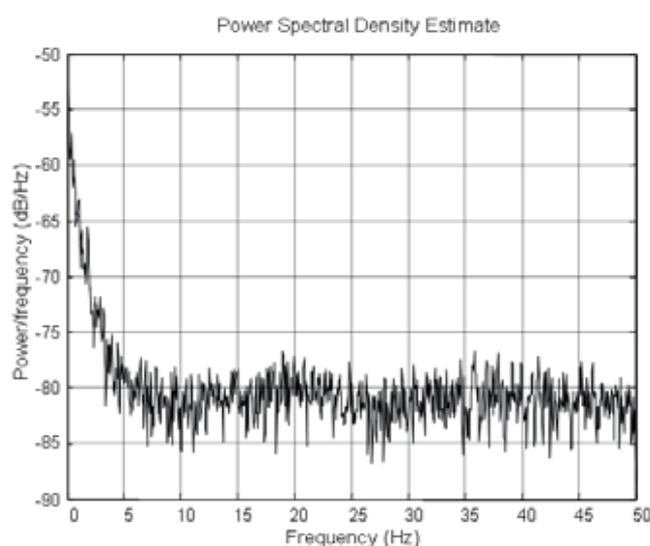


Fig 1. To model the noise present in the data profile we need to know the power spectrum density. This signal is used to obtain the filter coefficients to generate the synthetic noise.

An autoregressive model was applied to the experimental data tests to obtain a noise model. This model provided the filter coefficients to implement a synthetic signal.

The graphics Fig1 and Fig2 show the agreement between the power spectral density estimation of the experimental test signal and the synthetic noise model.

The resultant synthesized noise model is used to simulate the real instrumentation and environmental noise and analyze the denoising process to obtain the improvement for each wavelet family. To select the optimal mother wavelet, a computed test was developed. This test is a trial and error method which report us a matrix with the RMS error of the Thorpe displacement histogram between

