ACOUSTIC DETECTION OF SMALL- AND MID-SIZED SURFACE VESSELS IN VERY SHALLOW WATERS

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Abstract: *The detection, localization and tracking of surface vessels for monitoring purposes is of great interest in areas such as marine natural parks, where navigation is limited and should be controlled. Nowadays the presence of big-sized ships in an area of interest can be easily detected and accurately monitored either by radar or via AIS system. However, small vessels do not adopt the AIS system and some of them, in particular rubber boats, have very weak radar signature, hence may be missed by usual monitoring systems. In these cases an alternative useful surveillance method can be based on the detection of underwater acoustic noise radiated by vessels. The acoustic signatures of small- to mid-sized surface vessels (ranging from rubber boats to fishing boat and tugs) are much less investigated in literature than those of slow, big ships, and can be extremely diverse. This work describes a bench of detection methods optimized for small- and mid-sized boats, and compares the preliminary results achieved by their application to a preliminary set of at-sea data. Acoustic noise was recorded in September 2010 by a single hydrophone located close to the seabed in very shallow waters in the coastal area of the Isle of Pianosa, in the National Park of Arcipelago Toscano, Italy. This work is partially funded by EU within the context of the ARGOMARINE Research Project.*

Keywords: *Surface Vessel Detection, Small Vessel Characterization, Non Gaussian Noise*

1. INTRODUTION

The detection, localization and tracking of surface vessels for monitoring purposes is of great interest in areas such as marine natural parks, where navigation is limited and should be controlled. Nowadays the presence of big-sized ships in an area of interest can be easily detected and accurately monitored either by radar or via AIS system, which is becoming more and more extensively used. However, small vessels do not adopt the AIS system and some of them, in particular rubber boats, have very weak radar signature, hence may be missed by usual monitoring systems. In these cases a complementary surveillance approach can be based on the analysis of underwater acoustic noise radiated by vessels.

Noise radiated by big, slow ships, such as cargoes and tankers, has been extensively studied for many years: it is characterized by low frequency spectral content, with most of energy below 1 kHz, almost constant level below 100 Hz and a slope of 6dB/octave beyond, over which many spectral lines (fundamentals of few Hz and their harmonics) are superimposed, mainly due to blade rate, generator and diesel firing rate [1]. Source levels (SL) are generally high and range from 170 to 190 dB/1μPa @1m. The acoustic signatures of small- to mid-sized surface vessels (ranging from rubber boats to fishing boats and tugs) are much less investigated in literature, and can be extremely diverse; a general characterization may be the following: they commonly have lower levels that may range between 120 and 170 dB/1μPa @1m, and are characterized by a broader frequency content (up to several tens of kHz) and much higher fundamental frequencies (from hundreds of Hz up to 5-6 kHz). The spread of these characteristics makes the problem of classification quite complicated, and generally implies the need of selecting detection methods different from the conventional methods of ship acoustic detection, and customizing them for the particular problem.

This work describes detection methods optimized for small- and mid-sized boats, and compares the preliminary results achieved by their application to a preliminary set of real at-sea data. Acoustic noise was recorded in September 2010 by a single hydrophone located close to the seabed in very shallow water in the coastal area of the Isle of Pianosa, in the Park of Arcipelago Toscano, Italy. Future plans include to conduct further measurements under controlled conditions and different environment, and to extend the measuring systems to a pair of sparse, volumetric arrays of hydrophones configured according to tetrahedral geometries and deployed on the seabed at a certain distance, in order to be able also to precisely localize and track over time the noise sources detected.

2. ALGORITHMS FOR SURFACE VESSEL DETECTION

The acoustic detection of surface vessels is addressed. The selection of the most appropriate detection algorithms is based on the statistical characterization of background noise and signals of interest, which can be assumed as stochastic processes. Statistical analysis includes the estimation of all the statistical moments up to the fourth order and of the data histogram, in order to determine whether the process is Gaussian or not, and to model its probability density function (pdf) in a proper way to obtain a good model-data comparison between histogram and pdf model (Fig. 1). The problem of detecting a surface vessel from single-hydrophone measurements is formalized in terms of a binary hypothesis testing problem. The signal radiated from a vessel is assumed to be affected by additive, statistically independent ambient noise.

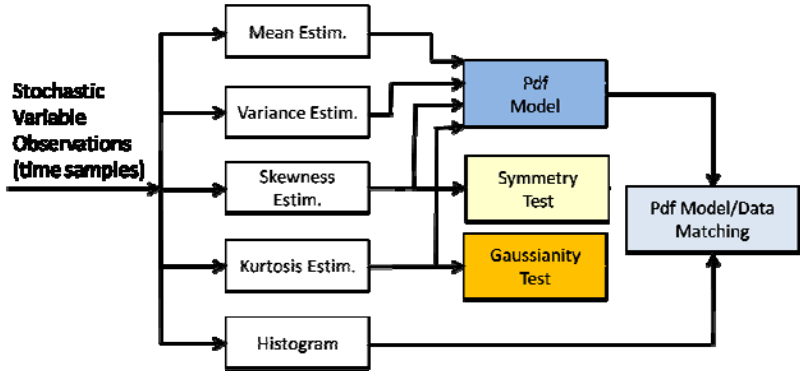

Fig.1. Block diagram of statistical analysis of acoustic noise observations.

The recorded discrete time series of N samples of data $\{y(t_k)\}$ corresponds to pure ambient noise $\{n(t_k)\}$ under the H_0 hypothesis; it is the sum of the signal of interest $\{s(t_k)\}$ and noise under the hypothesis H_1:

$$\begin{cases} H_0: & y(t_k) = n(t_k) \qquad k = 1,\dots,N \\ H_1: & y(t_k) = s(t_k) + n(t_k) \end{cases} \tag{1}$$

Both signal and noise are assumed stationary, zero-mean stochastic processes (at least over the N samples processed at once), and generally non Gaussian. As the problem is to detect any kind of unknown surface vessel in the area of measurement, no *a-priori* assumption about the signal shape or autocorrelation function can be made; hence, the approaches are limited to so-called *anomaly detectors* based on the computation of different variables, such as energy, or integrals of higher-order cumulants [2,3].

Both low-frequency ambient noise (particularly if dominated by ship traffic) and vessel signatures are traditionally considered highly non Gaussian and non linear [2]. In particular, the dominant sources of noise radiated by merchant ships are of hydrodynamic and mechanical nature. Among hydrodynamic phenomena, propeller cavitation and flow noise are the major ones; both are non linear. Mechanical-born noise derives from blade rate and propulsion machinery; also in this case processes is generally non linear, with one fundamental frequency and several harmonics. Fast motor-boats are expected to be characterized by much louder contribution of cavitation (wide-band, high-frequency component) than slow, big ships, which radiate many families of low-frequency, loud spectral lines, mainly located below 1 kHz.

Through second-order (i.e., Fourier) analysis only linear mechanisms can be studied, as supposed uncorrelation among harmonics implies suppression of phase information; whereas the major and most interesting property of the bispectrum, i.e., the third order cumulant, of a process is that it is nominally zero in the whole frequency domain if the process is Gaussian (hence linear). The bispectrum-based approach followed in this work derives from the detection test that Hinich proposed in [2], which works under the hypothesis of non-Gaussian signals in presence of non-Gaussian noise. Annex A.1 provides the definition of bispectrum for a stationary process and the selected estimation method. A block diagram describing the detection scheme is shown in Fig. 2, which is based on the evaluation of two different test variables obtained from data processing. The decision test selected is a Generalized Likelihood Ratio Test (GLRT). A GLRT scheme is applied to the decision variable λ^2_{BSP} based on bispectrum computation:

$$\lambda_{BSP}^2 = 2\frac{K^2L^2}{N}\sum_{(f_1,f_2)\in OAB}\frac{\left|\hat{B}_{y,av}(f_1,f_2)-\hat{B}_{n,av}(f_1,f_2)\right|^2}{S_y(f_1)S_y(f_2)S_y(f_1+f_2)}, \tag{2}$$

where $\hat{B}_{y,av}(f_1,f_2)$ and $\hat{B}_{n,av}(f_1,f_2)$ are consistent estimates of the bispectrum of the observed data and of pure ambient noise respectively; the frequency domain OAB, K and L are defined in Annex A.1; $S_y(f)$ is a consistent estimate of the observation's power spectral density. The second GLRT test is on the decision variable λ_{PS}^2:

$$\lambda_{PS}^2 = \sum_{k=1}^{N} y^2(t_k)/\sigma_n^2, \tag{3}$$

where σ_n^2 is the noise variance. In both cases the decision is for H_1 when the test variable overcomes a pre-defined threshold ($T_{c,BSP}^2$ and $T_{c,PS}^2$ respectively, which depend on a given probability of false alarm $P_{FA}=\alpha$). Details on the statistical analysis of the tests are in [2]. The fusion among the decision tests results obtained on the different variables is considered, so that the final decision D can be taken between H_0 and H_1.

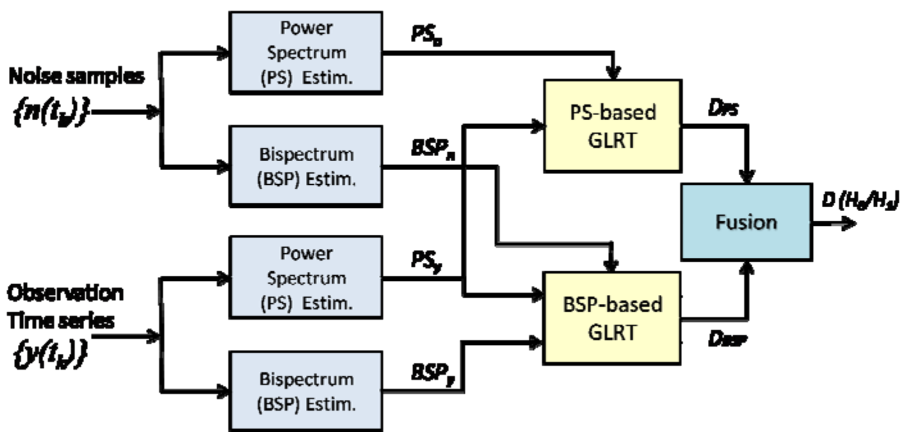

Fig. 2. Block diagram of the proposed detection scheme.

3. DESCRIPTION OF EXPERIMENTAL MEASUREMENTS AT SEA

Preliminary acoustic measurements of ambient noise and passages of surface vessels were conducted in a very shallow water environment (water depth around 8 m) with a single hydrophone located at 1m of height from the seabed, about 30 m from shore in an area characterized by patches of sand and patches of posidonia and by a pretty peculiar wedge bathymetry which will be discussed in Section 4.

The Power Spectral Density (PSD) function of two typical datasets (2-sec long each) are compared in Fig. 3, one in calm sea conditions (sea state between 1 and 2), the other one in bad sea conditions (sea state around 4); beyond 2 kHz the level difference is about 10 dB at average, in good agreement with Wenz curves. Below 2 kHz the PSD is lower in bad than calm sea conditions, presumably due to the lack of ship traffic. Table 1 shows the statistical analysis of the two ambient noise datasets, compared to the noise radiated by a mid-sized vessel; the second and higher order parameters are computed in the bandwidth 100Hz-18kHz. Evident deviation from Gaussianity is outlined by high values of kurtosis (equal to 3 for Gaussian variables). The comparison between data histograms and related probability density function (pdf) models is shown in Fig. 4. The pdf model is the Asymmetric Generalized Gaussian (AGG) [4] based on the parameters estimated in Table 1. Deviation from Gaussianity is confirmed by relatively peaked histogram shape.

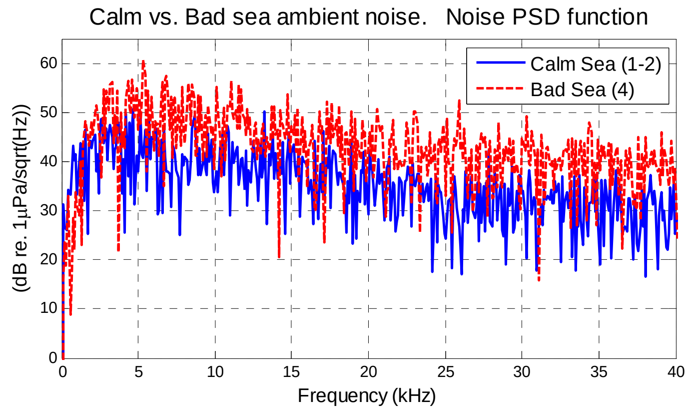

Fig.3. PSD functions of ambient noise computed over 2-sec-long datasets under different weather conditions (estimated sea state in brackets).

	Definition	*Calm sea*	*Bad sea*	*Vessel*
Variance	$\sigma_y^2 = E\{(y(t_k) - \mu_y)^2\}$	0.017	0.0015	0.006
Skewness	$h_y = E\{(y(t_k) - \mu_y)^3\} / \sigma_y^3$	0.17	-0.05	-0.05
Kurtosis	$\beta_y = E\{(y(t_k) - \mu_y)^4\} / \sigma_y^4$	3.7	4.3	3.5

Table 1: Statistical parameters: definition; values computed for three 2-sec-long data sets $\{y(t_k)\}$ over 100Hz - 18kHz bandwidth.

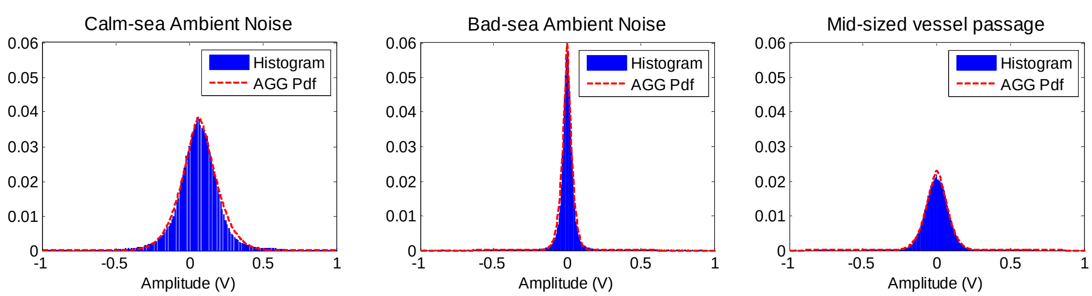

Fig. 4. Comparison of data histogram and pdf of the data sets analyzed in Table 1.

The hydrophone recorded the passage of various boats of different kinds, size and speed. The measurement bandwidth is from 100 Hz to 96 kHz; Figure 5 shows the spectrogram of passages of different vessels in the bandwidth below 20 kHz. All plots are characterized by intensity striation patterns which are typical of moving broadband sources and are due to constructive and destructive interferences of acoustic modes propagating in a shallow water environment [5]. The energy emitted by the mid-sized, slow vessel of Fig. 5(a) is limited to 5 kHz; the signature in Fig. 5(b) belongs to a faster boat with narrow spectral lines below 4 kHz but many fringes in the whole selected bandwidth. The signature in Fig. 5(c) belongs to a rubber boat accelerating and leaving in very short time; it is characterized by spectral lines and intensity fringes in the bandwidth below 4 kHz, and by a diffuse broadband noise due to strong cavitation phenomenon.

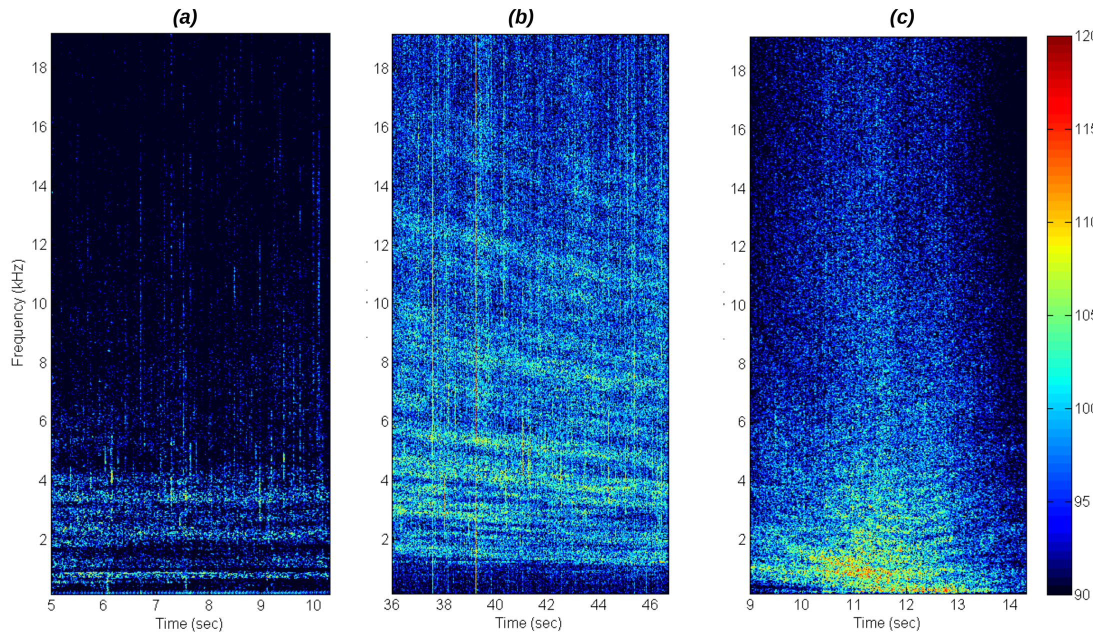

Fig. 5. Examples of acoustic noise measurements for different kinds of surface vessels. Spectrogram representation (dB re. 1μPa).

4. DETECTION RESULTS AND DISCUSSION

The decision variables λ_{PS}^2 and λ_{BSP}^2 are computed along the passage of a rubber boat (Fig. 6) and of a mid-sized vessel (Fig. 7) in the bands 100-800 Hz and 100-18000 Hz. The test thresholds are superimposed and identified by red dashed lines; P_{FA} is set to 1%. When the variable overcomes the threshold a vessel is detected. In Fig. 6 the rubber boat switched on its engine very close to the hydrophone (at 276.5 min), left and stopped. Before its appearance an unknown bigger ship appeared in the surroundings, as emphasized in plots (a) and particularly (c) of Fig. 6, that is only in the lower part of the bandwidth. In the case of the mid-sized vessel the navigation data were available and could be used to estimate the detection range. Maximum detection range achieved is very limited. This is probably due to the peculiar bathymetry and to the specific location of the hydrophone at the top of a wedge, as confirmed by the simulation obtained at 500 Hz by Bellhop propagation modelling tool on the basis of bathymetric data of the area and assuming an effective sediment simulating a sand-posidonia mix (Fig. 8). If the noise source is beyond the step (i.e. at ranges bigger than 350m), most of sound is trapped in the deeper part of the waveguide and absorbed by the slope. As expected, bigger, slow vessels are better detected over low-frequency sub-band while fast, small boats over much broader bands. Bispectrum seems to provide generally higher signal excess and to allow detection for slightly longer time than the conventional energy test.

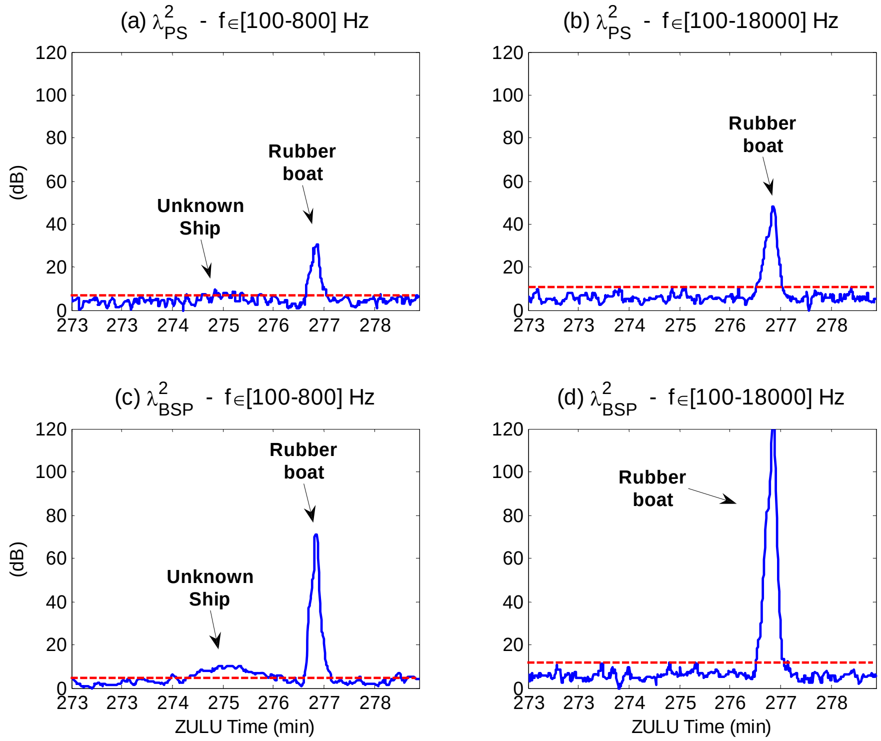

Fig. 6. Spectrum- (a)/(b) and bispectrum-based (c)/(d) test variables computed over two sub-bands while an unknown ship and a rubber boat pass in the area.

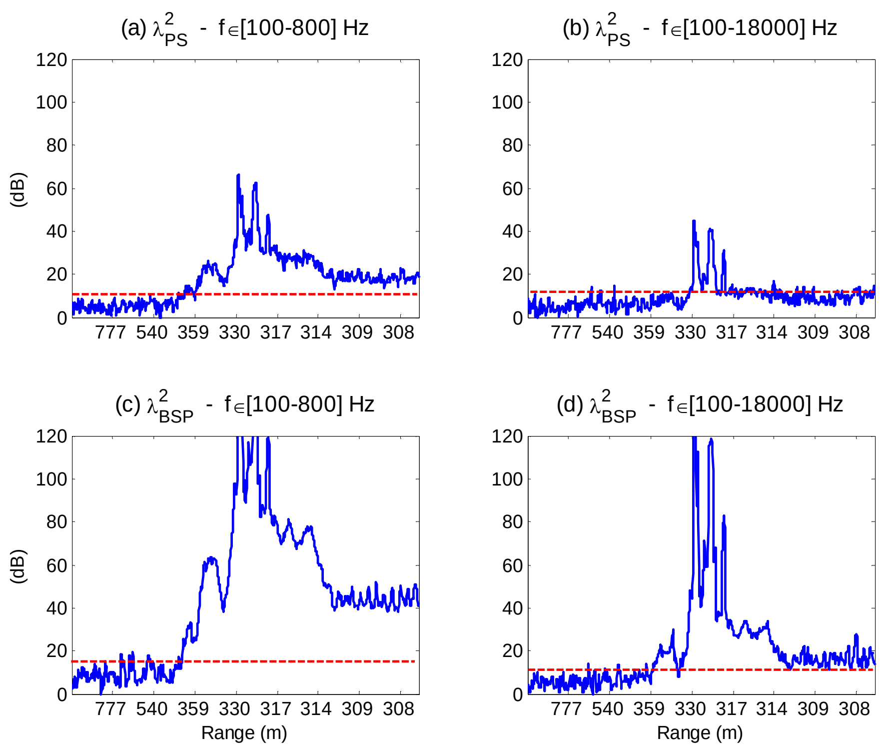

Fig. 7. Test variables detect a mid-sized vessel which approaches, manouvers and stops.

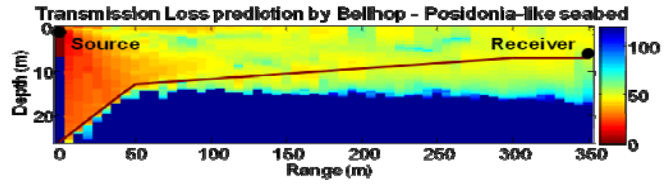

Fig. 8. Bellhop simulation when a noise source at 500 Hz is at the limit of the wedge.

5. ACKNOWLEDGEMENTS

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A1. BISPECTRUM DEFINITION AND ESTIMATION METHOD

In the third order statistics, correlation among three time sample values is estimated. Bispectrum of a discrete, stationary stochastic process $\{x(t_k)\}$ is defined as the double Fourier transform of the third order cumulant $c_x(t_i, t_k)$ [3]:

$$B_x(f_1, f_2) = \sum_{i=-\infty}^{\infty} \sum_{k=-\infty}^{\infty} c_x(t_i, t_k) \exp\{-j2\pi(f_1 t_i + f_2 t_k)\}, \quad (4)$$

with $c_x(t_i, t_k) = E\{x(t)x(t-t_i)x(t-t_k)\}$. Due to its symmetry and periodicity properties, the bispectrum of a stationary process has a triangular principal domain OAB, which, given the frequency pair f_j and f_k, is defined by $0 \le j \le \frac{N}{2};\ 0 \le k \le j;\ 2j + 2k \le N;\ f_j = \frac{j}{NT}, f_k = \frac{k}{NT}$, where T is the sampling period.

The selected consistent estimator is computed by dividing the time series into K pieces, averaging the piecewise sample bispectra and finally doing bifrequency smoothing on a square of LxL samples around each bispectrum value of the principal domain [3]:

$$\hat{B}_{x,av}(f_1, f_2) = \frac{1}{KL^2} \sum_{k=1}^{K} \sum_{r=-L/2}^{L/2} \sum_{s=-L/2}^{L/2} \hat{B}_x^{(k)}(f_{1+r}, f_{2+s}) \quad (5)$$

where $\hat{B}_x^{(k)}(f_{1+r}, f_{2+s})$ is the bispectrum estimator of the k^{th} segment of the data time series.