Proceedings of the Institute of Acoustics

FISH ECHOES CLASSIFICATION VIA AUTO-REGRESSIVE MODELLING

P. Degoul, P. Flandrin, N. Gache, M. Zakharia

I.C.P.I. Lyon, Labo T.S., UA 346 CNRS, 25 rue du Plat, 69288, Lyon, France

INTRODUCTION

Most of the echo-sounders and echo-integration systems use a relation between the echo energy and the fish size. This relation is commonly established using single-frequency (narrow-band) systems. Sometimes multiple frequency echo-sounders are used, but no correlation can be easily established between the information extracted for various frequency ranges.

In a natural environment the size estimation of an individual fish can be highly perturbed by the fish movement. The same problem arises for fish schools.

Our approach of the problem is a wide-band impulsive one (all frequencies all over the transducers bandwidth are emitted simultaneously). In this paper we will describe and interpret an experiment done on individual live fish in a pool (controlled position and behaviour). In our experiment, echoes are obtained from fishes of various size and same species; frequency ranges from 50 kHz to 80 kHz. The impulse responses are stored as a sequence of 60 consecutive echoes of the same fish for various behaviour. They show important variations in both time and frequency domain (especially for wild fish). The echoes are analysed, via Auto-Regressive modelling, in order to reduce the amount of information they contain.

Classification attempts have been done using various parameters of the model. The classification based on cepstral distance (commonly used in speech processing) seems to be well matched to this application. The results show the interest of adding "spectral signature" information to the classical energy information, in order to increase the size classification performance.

EXPERIMENTAL EVALUATION

The experiment is described in Figure 1: the live fishes (same species, tenches, Tinca tinca, various sizes: 10 to 35 cm) were fixed individually in the transducer beam (main lobe on the acoustical axis) by thin nylon threads. Thread tightness was used to control the freedom of movement. Echoes were recorded for a variety of fish behavioural conditions from a very quiet situation (after a long immersion time, about 15 hours) to very active ones. The fish was observed visually while recording the sequences. Comments, on behaviour, were also stored on the tape recorder. The distance from the transducer to the fish was about one metre; it could vary during active behavioural sequences (the fish could also move slightly in the beam).

The emitted signal is a 5 μs pulse with a repetition rate of 140 ms. The operating frequency of the transducers ranges from 50 to 75 kHz. The echoes were amplified (overall gain of 100), time-gated and filtered (400 Hz to 200 kHz) before being recorded. The echoes were digitized subsequently and stored on a personal computer[1],[2].

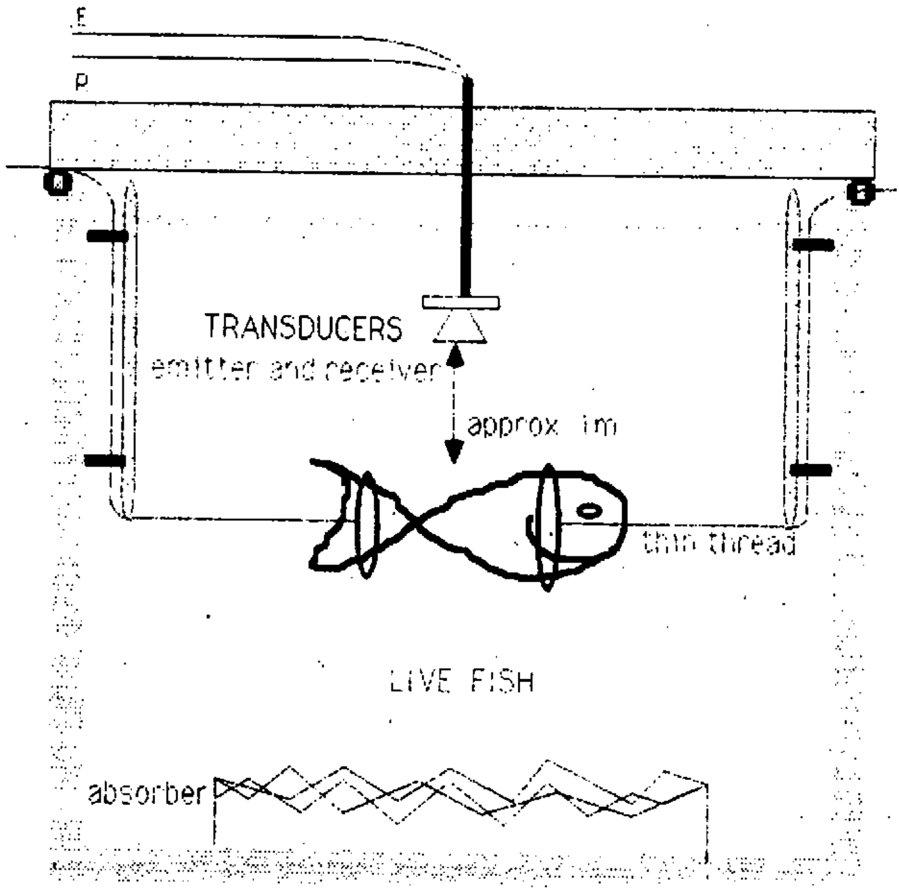

Figure 1 Experiment description[1].

SOME EXAMPLES

Figures 2 and 3 show examples of echo representation: impulse response and transfer function (power spectrum) in the case of a calm fish (Figure 2) and a wild one (Figure 3). These figures show a great variability in both domains (time or frequency) for wild fish.

Figures 4 and 5 show the energy (overall bandwidth) distribution of the echoes of the sequences (60 echoes) corresponding to Figures 2 and 3. They illustrate the difficulty in establishing a precise relation between the fish size and the echoes energy, even in the case of wide-band responses[2],[3].

Other sequences show the same influence of the fish behaviour on the reflected echoes energy. The results show the need of a less crude approach to the spectral analysis of the echoes.

MOTIVATION FOR A MODELLING APPROACH

Once the usefulness of taking in account frequency information is recognized[1], [3], the problem is to get access to such information. This is in fact twofold since:

(i) the wanted procedure must catch significative spectral features which
(ii) can be used "efficiently" for classification.

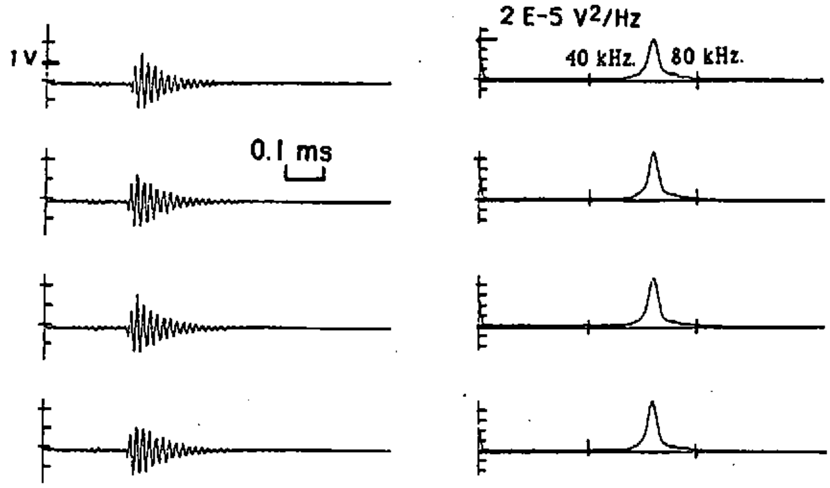

Figure 2 Echo sequence example; calm fish[1],[3].

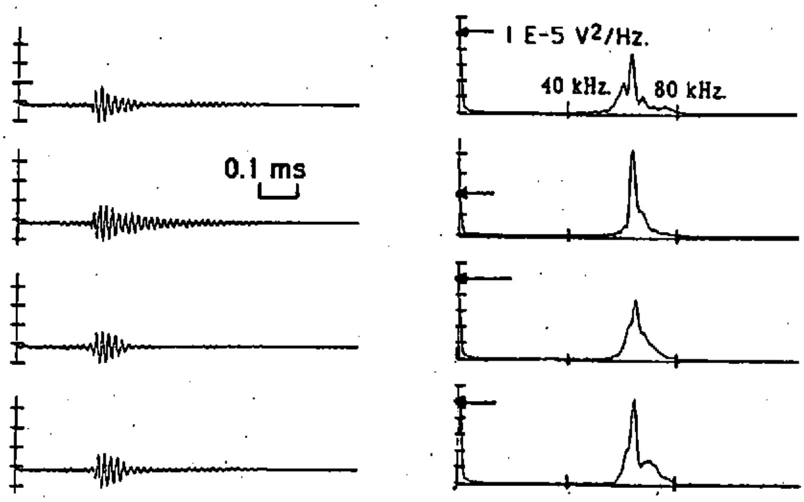

Figure 3 Echo sequence example; wild fish[1],[3].

FISH ECHOES CLASSIFICATION VIA AUTO-REGRESSIVE MODELLING

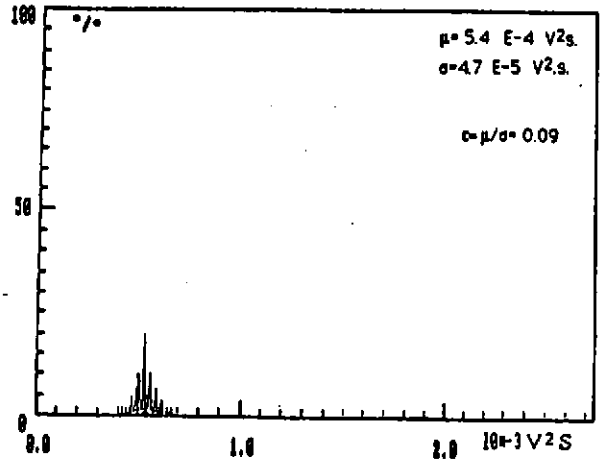

Figure 4 Energy distribution; calm fish (→ Figure 2).

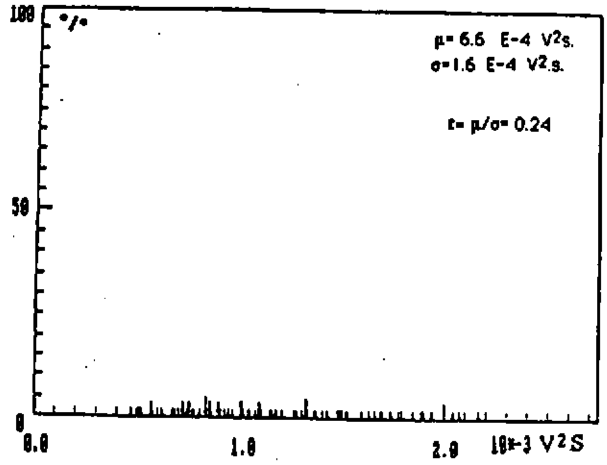

Figure 5 Energy distribution; wild fish (→ Figure 3).

A parsimonious frequency representation is then needed, in order to summarize relevant information in a reduced number of parameters. When no a priori information is given on the analyzed signals an intuitive solution is to make use of a (non-parametric) Fourier Transform (Figures 2 and 3) and to use the Fourier coefficients for a classification. This approach is similar to multiple frequency analysis. In a classification context, this will present the drawback of not ensuring any parsimonious representation. An improvement can be provided if it is possible to assume some likely a priori structure for the analyzed signals. In this case, a parametric model can be used, which has to be identified. The overall improvement over a "blind" (Fourier type) analysis is then related to the degree of fitness which exists between the assumed model and the data.

CHOICE AND IDENTIFICATION OF THE AUTO-REGRESSIVE MODEL

Considering fish echo sequences (like Figures 2 and 3), relevant frequency information can be described by peaks (location and heights) in the power spectrum (or frequency resonances). It is well known[5] that the relevant model for such a situation is the so-called Auto-Regressive (AR) model: if the analyzed time series (x_n) (signal samples, with a sampling rate chosen arbitrarily as unity) is supposed to be an AR signal it will satisfy the expression:

$$x_n + \sum_{k=1}^{p} a_k x_{n-k} = e_n$$

where:

-(e_n) is a microscopic correlation sequence (flat spectrum of height σ^2).

-p is the order of the model.

-$a_1, \ldots, a_p$ are the AR coefficients.

Such a signal can be viewed as the output of a recursive filter whose input has flat spectrum. It follows that all the frequency information on the filter is contained in the AR coefficients and, in fact, the power spectrum $S_x(f)$ of the analyzed signal expresses as[5]:

$$S_x(f) = \frac{\sigma^2}{\left| 1 + \sum_{k=1}^{p} a_k e^{-j\,2\pi kf} \right|^2}$$

This corresponds to an all-pole filter and, as a consequence, to peaks in the spectrum. The location and the heights of these peaks are respectively related to the modulus and the phase of the roots (w.r.t the complex variable $z = \exp(j2\pi f)$) of the squared polynomial quantity in the above equation. These roots are the poles of the model.

Identification of an AR model is achieved when picking the set of coefficients $\{a_1, \ldots, a_p, \sigma^2\}$ which best describe the observed data. Using a mean-square error minimization as an optimality criterion leads to efficient algorithms[5] which can be put in a recursive form w.r.t. the unknown order p. The final identification is completed when finding an order which ensures a global error minimization.

CLASSIFICATION WITH AR MODELS

Given an observed signal, AR modelling provides a structural characterization by means of the set $\{a_1, \ldots, a_p, \sigma^2\}$. The parameters could be used directly for a classification, given a distance measurement, e.g.:

$$d_1 = \sigma^2 - \sigma^2_{ref.} + \sum_{k=1}^{p} (a_k - a_{k\ ref.})^2$$

where $\{a_{1ref.}, \ldots, a_{pref.}, \sigma^2_{ref.}\}$ would be a reference set associated to a well-known situation. However, it turns out that this classification presents little interest in terms of performances because, being interested in the frequency features, these are encoded only indirectly in the AR coefficients. Better results can be obtained by using new sets of parameters which are more directly related to the frequency characteristics of the echoes. These parameters can be derived from the AR coefficients. Among different possibilities (poles, reflection coefficients[5],[6]), special emphasis can be put on the so-called cepstral coefficients. In fact, we can use as a distance measurement, the quantity:

$$d_2 = \int_{-1/2}^{+1/2} \left| \ln\{S_x(f)\} - \ln\{S_{ref.}(f)\} \right|^2 df$$

where $S_{ref.}(f)$ stands for the power spectral density of the reference (to which the analyzed signal is compared). This is a direct comparison of the (modelled) spectra in decibels. It turns out[6] that, in the AR case, the distance d_2 can be approximated by:

$$d_2 = (C_0 - C_{0ref.})^2 + 2 \sum_{k=1}^{K} (C_k - C_{kref.})^2$$

where the C_k are the so-called cepstral coefficients. The first coefficient, $C_0 = \ln(\sigma^2)$, is directly related to the energy, whereas the other ones can be derived from the AR coefficients in a recursive manner[6]:

$$C_1 = -a_1$$

$$C_j = -a_j - \sum_{k=1}^{j-1} \frac{k}{j} C_k \, a_{j-k}; \qquad j = 2,\ldots, p$$

$$C_j = - \sum_{k=1}^{p} (1 - \frac{k}{j}) \, C_{j-k} \, a_k; \qquad j = p+1,\ldots, K$$

The order K is chosen such that the remaining coefficients (C_k, $k>K$) are negligible.

APPLICATION TO ECHO CLASSIFICATION

The algorithm used for echo modelling is the Levinson algorithm[5]. The error criterion for selecting the model order is the Final Prediction Error (FPE) criterion[5]. The order has been set up to 12 to obtain a satisfactory compromise for all the analyzed echoes. Figure 6 shows an example of echo modelling: pole diagram in the unit circle, time representation, modelled power spectrum.

Fishes have been classified in 3 sizes: small (less than 10 cm), medium (10 to 20 cm) and large (20 to 30 cm). Their behaviour has been also classified in 3 categories: still fish, live fish and wild fish. The total amount of echoes is 4740 (79 sequences of 60 echoes). For given sequences, the echoes with an odd number have been used to establish a reference (learning phase). The echoes with an even number have been then classified using reference vector proximity. The reference was obtained from the average value of the parameters.

Table 1 give the number of reference echoes used for size classification and the number of trials.

SIZE	NUMBER OF REFERENCE ECHOES	NUMBER OF TRIALS
SMALL	150	210
MEDIUM	300	180
LARGE	450	570
TOTAL	900	960

TABLE 1: SIZE CLASSES

Table 2 gives the percentage of success (good classification) for three different sets of parameters:

-A: cepstral parameters including c_0 (spectral signature and energy).
-B: cepstral parameters excluding c_0 (spectral signature).
-C: c_0 (energy).

SIZE/SUCCESS	A	B	C
SMALL	99.6%	98.6%	97.2%
MEDIUM	84.5%	72.7%	72.7%
LARGE	91.3%	88.9%	82.5%
TOTAL	**92%**	**88%**	**84%**

TABLE 2: SIZE CLASSIFICATION RESULTS

The same classification work has been done on behavioural echo variation. The data and the results are summarized in Table 3 (A case).

SIZE	NUMBER OF REFERENCE CODES	NUMBER OF TRIALS	SUCCESS PERCENTAGE
QUIET	210	450	62.2%
LIVE	420	300	19.4%
WILD	630	210	70.6%
TOTAL	**1260**	**860**	**51%**

TABLE 3: BEHAVIOUR CLASSIFICATION

The results show clearly the interest of using a "spectral signature" of the echoes for size classification. This information alone can provide a success percentage (88%) higher than the one obtained with the energy alone (84%). Combining the information can lead to a very good classification result: 92% of success (for 960 trials). The results obtained on behaviour classification are less interesting (51% of success). Combining both classifications leads to a success percentage of 65% (for 960 trials). Success percentage are still higher for size classification (95%), 85%, 51%) than for behaviour classification (69%, 53%, 83%).

CONCLUSION

We have shown the interest of using a "spectral signature" of wide-band echoes for classification purpose. The signature based on auto-regressive modelling and the classification based on cepstral distance give a high success rate for size classification. Behaviour classification results are less relevant. This can be due to two main reasons; the first reason is the correlation between fish size and its behaviour and a lack of uncorrelated data for some classes. The second reason can be due to the classifying patterns used: average values of characteristic parameters; the behaviour information can be indeed contained in the variations (variance) of the parameters and not only in their mean value.

Anyway, such an analysis can be very interesting when looking only for size information (which is the case of most echo-sounders). In this case, fish behaviour is a perturbing parameter, and the bad behaviour classification performances can be interpreted, in this case, as a robustness on the size estimation.

ACKNOWLEDGEMENTS

The experiments have been done in CNRS LMA, labo US in Marseille, France. The authors wish to thank Mr. Canda A., for helping in processing data. This work was supported by IFREMER, Centre de Brest, FRANCE.

REFERENCES

[1] M. ZAKHARIA: "Variations of fish target strength induced by its movement; a wide-band impulse experiment." Rapp. P.-v. Réun. Cons. int. Explor. Mer (to be published).
[2] A. CANDA: "Etude des relations entre la taille d'un poisson et ses échos sonar." Rapport de stage de D.E.A. ICPI Lyon, INSA Lyon, FRANCE, Sept. 1987.
[3] M. ZAKHARIA: "Systèmes acoustiques large-bande en pêche." Journées scientifiques et techniques en acoustique sous-marine. ISSN 0750-7356. CNRS, LMA, Marseille, FRANCE, Oct 1988.
[4] P. DEGOUL: "Méthodes de modélisation auto-régressive des signaux. Application à la classification d'échos de poissons." Rapport de stage de D.E.A. ICPI Lyon, INSA Lyon, FRANCE, Sept. 1988.
[5] S. M. KAY: "Modern Spectral Estimation." Prentice-Hall, 1987.
[6] A. H. GRAY Jr., J. D. MARKEL: "Distance measures for speech processing." IEEE Trans. on ASSP, ASSP-24(5), pp.380-391, 1976.

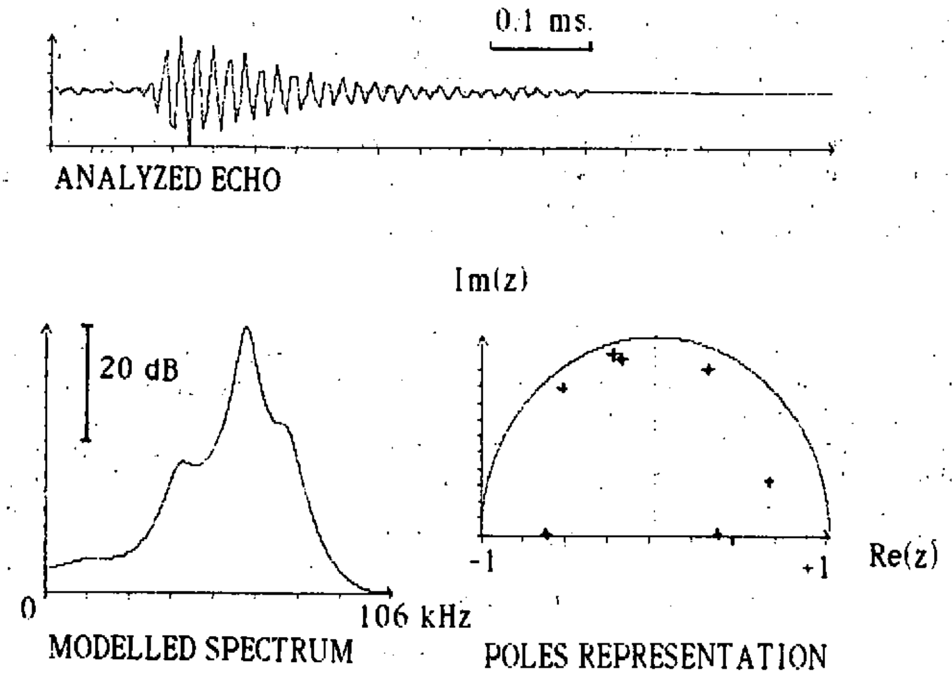

Figure 6 Example of echo modelling [4].