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Analysis of indirect '*in situ*' fish target-strength estimation methods

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ABSTRACT

The paper analyzes existing *in situ* methods of fish target-strength estimation with special emphasis on an indirect method that utilizes statistical manipulation on a backscattered acoustic echoes set. The inverse problem in question requires finding the unknown probability density distribution (PDF) of target strength in the logarithmic „domain" or PDF of a backscattering cross-section in the „domain" of absolute variables. These PDFs can be estimated by solving the so called „single-target single-beam integral equation", relating distributions of echo variable, target strength and beam pattern of the echo sounder transducer. In the presented analysis special attention is given to four newly developed TS-estimation methods, viz.: Expectation, Maximization and Smoothing (EMS), Discrete „Mellin Deconvolution", Windowed Singular Value Decomposition (WSVD) and Regularization. These methods use more sophisticated estimation techniques than conventional deconvolution and related methods. A comparison of the resulting estimates obtained from the analyzed methods (using simulations as well as real data from acoustic surveys) concludes the paper.

1. INTRODUCTION

To assess fish abundance from acoustic surveys, a target strength (TS) or back-scattering cross-section (σ_{bs}) of individual fish must be known to properly scale an echo integration output [8],[16],[28]. Therefore, reliable estimates of the average fish target strength are indispensable to convert echo integration data to absolute estimates of fish density and hence population estimates. Also, these TS estimates are required to assess sampled volumes in echo counting techniques [14]. Moreover, variations in mean TS are thought to be among the dominant sources of non-survey errors in acoustic population estimates derived from echo integration whose accuracy and precision are mostly determined by the performance of mean target strength estimates [16].

TS estimation methods can be classified into three principal groups [9]:

(i) theoretical;

(ii) *ex situ* measures on dead or alive fish under controlled (experimental) conditions;

(iii) *in situ* measures on free-swimming fish in their natural habitat.

A search of the literature suggested [9],[10],[26] that TS data obtained from the theoretical and *ex situ* methods may in many cases be not reliable and consistent with *in situ* results as many factors are likely to influence fish target strength (migration, aspect, behaviors, physiological state) and may differ from time to time and place to place. Due to these reasons, the measurement of fish TS *in situ*, wherever possible, was thought to be the most reliable and optimal TS estimation strategy [6],[12].

As it is known, *in situ* methods of TS measurement require removing the effect of the unknown random location of fish in the acoustic beam $b(\theta,\varphi)$ - i.e. removing the so called beam pattern factor[6]. This can be realized either directly from each individual echo, or indirectly by processing a collection of individual echoes. Direct methods are generally more complex and costly than indirect techniques because they require a special configuration of the transducer providing multiple beam (dual-beam, or split-beam) and multi-channel echo sounder receiver [6],[21],[27].

Indirect techniques are attractive because they can be implemented with the same single-beam, and single-channel echo sounder as used for routine echo integration surveys, but they require knowledge of the transducer's beam pattern and assume uniform distribution of fish in a sampled volume that might be often not the case [6],[9]. Indirect methods can be either parametric - using a TS probability distribution function (PDF) with relatively few parameters, or non-parametric - in which the number of estimates equals the number of observations.

2. SURVEY OF EXISTING INDIRECT '*IN SITU*' TS-ESTIMATION METHODS

Commonly researches credit Craig and Forbes [4] for the formulation of the statistical inverse treatment for estimating fish target strength by statistical correction of the measured echo level PDF to the target strength PDF, using directivity PDF - represented by circular areas covered by cross-sections of the beam pattern. The proposed method is a non-parametric method in the logarithmic, or dB, domain and uses a set of linear equations, the solution of which gives the required estimate of TS distribution. The estimates obtained by the Craig-Forbes method are in general worse than those from other methods (particularly for bimodal distributions) and are strongly dependent on the actual TS distributions [6],[26].

The next method was developed by Ehrenberg [6], who formulated the inverse problem of TS estimation in terms of a Volterra integral equation of the first kind and used an nth-degree polynomial approximation to solve it for the unknown back-scattering cross-section PDF. The unknown polynomial coefficients were evaluated simultaneously by a least square fit. The drawback of the method is its ability to generate ill-conditioned simultaneous equations for the higher degree polynomials that make it difficult to obtain accurate estimates of TS distribution.

Robinson [23] modified the Ehrenberg estimation technique by subdividing the $p(\sigma_{bs})$ estimate space into a number of sub-intervals and fits low order polynomials (of $n < 3$) to the unknown back-scattering cross-section distribution. The polynomial coefficients were determined as in the Ehrenberg method by least squares. For the actual PDFs with a larger standard deviation (> 2.5 dB) the simultaneous equations to be solved may become ill-conditioned, as in the Ehrenberg method that may result in underestimating the mean target strength [23]. Robinson also found that higher amplitude thresholds cause a more positive bias in TS and that modal artifacts are possible with his method due to fitting multiple cubics.

Parametric methods were introduced by Petersen and Clay [3] and further modified by Ehrenberg [7]. Petersen and Clay used the Rayleigh PDF to model the unknown distribution $p(\sigma_{bs})$ and integrated the integral equation with respect to the beam pattern factor. The Rayleigh PDF was justified by theoretical reasons (central limit theorem) and the parameter was fit by least squares. The technique adjusts the unknown parameter in the Rayleigh distribution until this theoretical PDF for the echo amplitudes and measured histogram most closely agreed. The advantage of assuming a particular distribution for σ_{bs} is that it should be easier to estimate a parameter of an underlying PDF than it is to estimate the entire PDF. However, these techniques should only be employed when Rayleigh-distributed on-axis pressure envelope hold. Ehrenberg [7] also used the Rayleigh distribution and an incomplete gamma function technique to express an acoustic integral equation. He also derived a general expression for the beam pattern factor PDF, and noted that the Rayleigh assumption is only valid for fish length to a wavelength ratio greater than 25. Clay and Heist [3] found that a two-parameter Rice PDF was justified and that fish activity and length both condition the Rice parameters.

Lindem [15] modified the Craig & Forbes method by setting all negative estimates to zero. He correlated fish length with modes in the indirect estimates.

Clay [2] formulated the Craig &.Forbes method in terms of deconvolution of PDFs. The „single-beam" integral equation was first formulated in terms of voltage and converted to a convolution integral by a change of variables. The .numerical deconvolution has been implemented using the *Z*-transform polynomial long division. Clay showed a correspondence between acoustic modes and fish species groups and advised that the technique was useful to estimate any acoustic size PDF. However, the deconvolution of actual data demonstrates oscillations and drifts in the results, especially for small echo amplitudes and low signal-to-noise ratio [2].

Miinalainen and Eronen [18] used a least-squares method but concluded that the use of non- negative least-squares for deconvolution was too time intensive and subject to noise. Instead they used a modified singular value decomposition (SVD) routine in which all negative values in the solution were converted to zeros [12].

Rudstam et al. [24] and Jacobson et al. [13] used Clay's deconvolution with Rice PDFs fitted *a posteriori* to the estimation of fish target strength and density. The use of Rician PDF is questionable because bumpiness in deconvolved data could be artifactual, but not the result of a combination of Ricians (fitted for fish size groups) [12]. These artifactual modes are inherent to all deconvolution techniques and may be treated as a result of undersampling of data. On the other hand, *a posteriori* techniques and parametric techniques presume knowledge of the fish scattering model which may not be available. Therefore parametric methods can be over-constrained by the target strength PDF model and so are not robust.

In general, although conventional deconvolution techniques can suffer from modal artifacts, if large sample sizes are provided, they offer better estimates as negative values of estimates are then largely avoided.

3. ANALYSIS OF NEWLY DEVELOPED INDIRECT TS-ESTIMATION METHODS

The recently developed target strength estimation methods are in general more complex and more sophisticated than deconvolution and other conventional techniques, but by this cost they partly avoid the problems of ill-conditioned equations and related problems with a matrix inversion. For instance, to avoid ill-conditioning a Singular Value Decomposition (SVD) method replaces inverse matrix by pseudoinverse, which eigen values, if too small, are replaced by zeros [20].

In addition, some of these methods , viz.: a subclass of iterative techniques which consists of Expectation, Maximization and Smoothing (EMS) and Maximum Entropy Regularization (MER) methods allow avoiding negative-valued solutions of a discrete form of a „single-target integral equation" by superimposing proper constraints on solutions obtained by iterations [12], [11],[20].

The most promising among these state-of-the-art methods which are subject of further analysis and comparison are:

- Discrete Mellin Transform (DMT) method [19],[20],
- Expectation, Maximization and Smoothing (EMS) method [12],[25],
- Windowed Singular Value Decomposition (WSVD) method [20],[11],
- Tichonow Regularization method [30],
- Maximum Entropy Regularization [11],[20]

3.1. DISCRETE MELLIN TRANSFORM

Estimation of the backscattering cross-section σ_{BS} from fish echoes requires a computation of the probability distribution function (PDF) which for the product of two random variables $\underline{z} = \underline{x}\,\underline{y}$ may be expressed by a „single-target integral equation"[19]:

$$f_z(z) = \int_0^{\infty} f_x(z/x) f_y(x) dx / x \qquad (1)$$

which rewritten for acoustic variables (e = $\sqrt{\sigma_{bs}}$ b) comes down to a pair of equations:

$$p_e(z) = \int_0^1 p_{\sqrt{\sigma_{BS}}}(z/x) p_b(x) dx / x \qquad (2a)$$

$$p_e(z) = \int_0^\infty p_b(z/x) p_{\sqrt{\sigma_{Bs}}}(x) dx / x \qquad (2b)$$

which can be solved with the use of the Mellin transform defined as [19]:

$$F(s) = M\{f(t)\} = \int_0^\infty f(t) t^{s-1} dt, \qquad (3a)$$

where $s = \alpha + j\beta$

$$f(t) = M^{-1}\{F(s)\} = \frac{1}{2\pi j}\int_{\sigma - j\infty}^{\sigma + j\infty} F(s) t^{-s} ds \quad (3b)$$

In the domain of the Mellin transform, the integral equation (1) takes the form of transforms product:

$$F_Z(s) = F_X(s) F_Y(s) \qquad (4)$$

which leads to the solution of the equation (1) in the form:

$$f_x(x) = M^{-1}\left[M\{f_z(z)\} / M\{f_y(y)\}\right] \qquad (5)$$

Due to the analogy to the convolution integral which for the Fourier transform corresponds to the transforms product, the integral equation (1) was called the „Mellin convolution" which in the domain of the PDF's can be written as:

$$f_z(z) = f_x(x) \underset{M}{*} f_y(y) = \int_0^\infty f_x(x) f_y(z/y) dx / x \quad (6)$$

where the asterix symbol $\underset{M}{*}$ marks the „Mellin convolution" as defined above.

Numerical computations of Mellin transforms by FFT algorithms [19] lead to a non-uniform sampling of PDFs. The problem can be avoided if we notice that the direct Mellin transform resembles the formula for statistical moments of PDF. Hence if $f(x)$ represents the PDF of a random variable taking positive values and the complex variable s belongs to the set of natural numbers $s \in \{N\}$, then the Mellin transform represents a series of moments of the random variable $\underline{x}$.

$$F(s) = \int_0^\infty x f(x) dx = m_{s-1} \qquad (7)$$

and for s = 1 the value of the transform can be treated as a moment of zero order of a normalized distribution function *f(x)*:

$$F(1) = \int_0^\infty f(x) dx = 1 = m_0$$

In the case of discrete random variables, the system of equations can be generalized by introducing a discrete Mellin transform (DMT) which on the real positive semi-axis represents a sampled continuos Mellin transform. Hence we have:

$$F(n) = \sum_{i=1}^{N} x_i^{n-1} f(x_i) \qquad (8)$$

On the other hand, the same moments of the random variable $\underline{x}$ can be computed with the use of the mean value estimator for realization of the random variable:

$$\hat{m}_n = \frac{1}{N}\sum_{i=1}^{N} x^n{}_i \qquad (9)$$

Considering the formula (5) and treating the moments as discrete Mellin transforms, we obtain the relation which links the moments of the three variables in consideration:

$$\mathbf{m}_x = \frac{\mathbf{m}_z}{\mathbf{m}_y} \qquad (10)$$

where $\mathbf{m}_z$ represents a series of moments of the measured echo amplitude („off-axis" voltage) which can be computed using the estimates given in the equations (9). The series $\mathbf{m}_y$ represents moments of the beam pattern PDF, and can be obtained with the use of the DMT. The result of dividing the above moments gives the first solution stage, that is knowledge of the series $\mathbf{m}_x$ of moments of the unknown backscattering cross-section („on-axis" voltage).

Fig. 1 illustrates the described concept of using the Discrete Mellin Transform along with statistical moments of the back-scattering cross-section random variable as applied to the estimation of its PDF. The presented two-dimensional plot of DMT on a complex plane $s = \alpha + j\beta$ refers to the Rayleigh distribution of the parameter $\sigma = 0.5$. Note that the zero-order and first order moments of the considered PDF are represented by samples of the DMT plot at $\alpha = 1$ and $\alpha = 2$.

In the second (inverse) stage we reconstruct the unknown PDF from moments which at the same

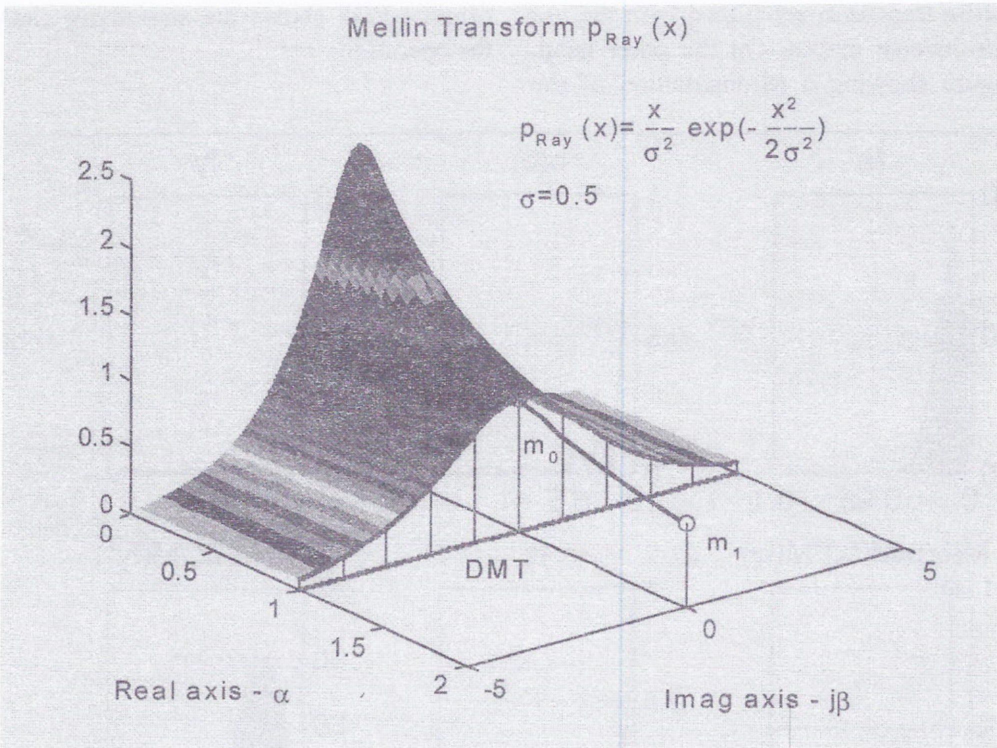

Fig. 1. Discrete Mellin Transform of Rayleigh PDF and interpretation of its two first moments

time constitutes a problem of defining the inverse Mellin transform. Considering the definition of moments of the discrete random variable:

$$m_n = \sum_{i=1}^{N} x_i^n P(x_i) \qquad (11)$$

this problem requires solving Vandermode's matrix:

$$\begin{bmatrix} 1 & 1 & 1 & \dots & 1 \\ x_1 & x_2 & x_3 & \dots & x_m \\ x_1^2 & x_2^2 & x_3^2 & \dots & x_m^2 \\ .. & .. & \dots & \dots & \dots \\ x_1^n & x_2^n & x_3^n & \dots & x_m^n \end{bmatrix} \begin{bmatrix} P_x(x_1) \\ P_x(x_2) \\ P_x(x_3) \\ \dots \\ P_x(x_m) \end{bmatrix} = \begin{bmatrix} m_{0,x} \\ m_{1,x} \\ m_{2,x} \\ \dots \\ m_{n,x} \end{bmatrix} \qquad (12)$$

in which:

$\mathbf{m_x}$ - moments estimates of unknown PDF's,

x_i - predicted centers of the histogram bins,

$P_x(x_i)$ - estimates of unknown PDF's.

The above matrix equation is ill conditioned because the matrix on the left side of the equation in generally does not have to be a square matrix, and both, the Gaussian elimination method and the LU decomposition give incorrect solutions [19]. One method of solving this problem is application of the singular value decomposition SVD which leads to obtaining a pseudo-inverse matrix that guarantees a solution with a minimum mean-square error [17]. By rewriting the equation (12) in the general matrix form:

$$\mathbf{Xp} = \mathbf{m} \qquad (13)$$

we can get the solution

$$\mathbf{p} = \mathbf{X}^{\#}\mathbf{m} \qquad (14)$$

where matrix $\mathbf{X}^{\#}$ is a pseudo-inverse matrix computed numerically using the SVD algorithm:

$$\begin{aligned} \mathbf{X} &= \mathbf{USV}^T = [\mathbf{U}]diag(w_i)[\mathbf{V}^T] \\ \mathbf{X}^{\#} &= \mathbf{US}^{-1}\mathbf{V}^T = [\mathbf{U}]diag(1/w_i)[\mathbf{V}^T] \end{aligned} \qquad (15)$$

in which the matrices $\mathbf{U}, \mathbf{V}$ are orthonormal, and the diagonal matrix $\mathbf{S}$ represents the singular values of matrix $\mathbf{X}$. The equation (14) represents simultaneously the matrix form of an inverse Discrete Mellin Transform, optimal in the sense of minimizing the mean-square error.

Fig. 2 shows the simulation result of testing the performance of DMT[19]. In this experiment the Rayleigh pseudo-random generated histogram was used as an estimate of the backscattering cross-section PDF. Function f_z obtained as the result of the „Mellin convolution" contains visible effects of the inverse Mellin transform calculated with the use of a pseudo-inverse matrix. On the other hand, the last figure showing a reconstruction of the original PDF shows the smoothing character of the operation.

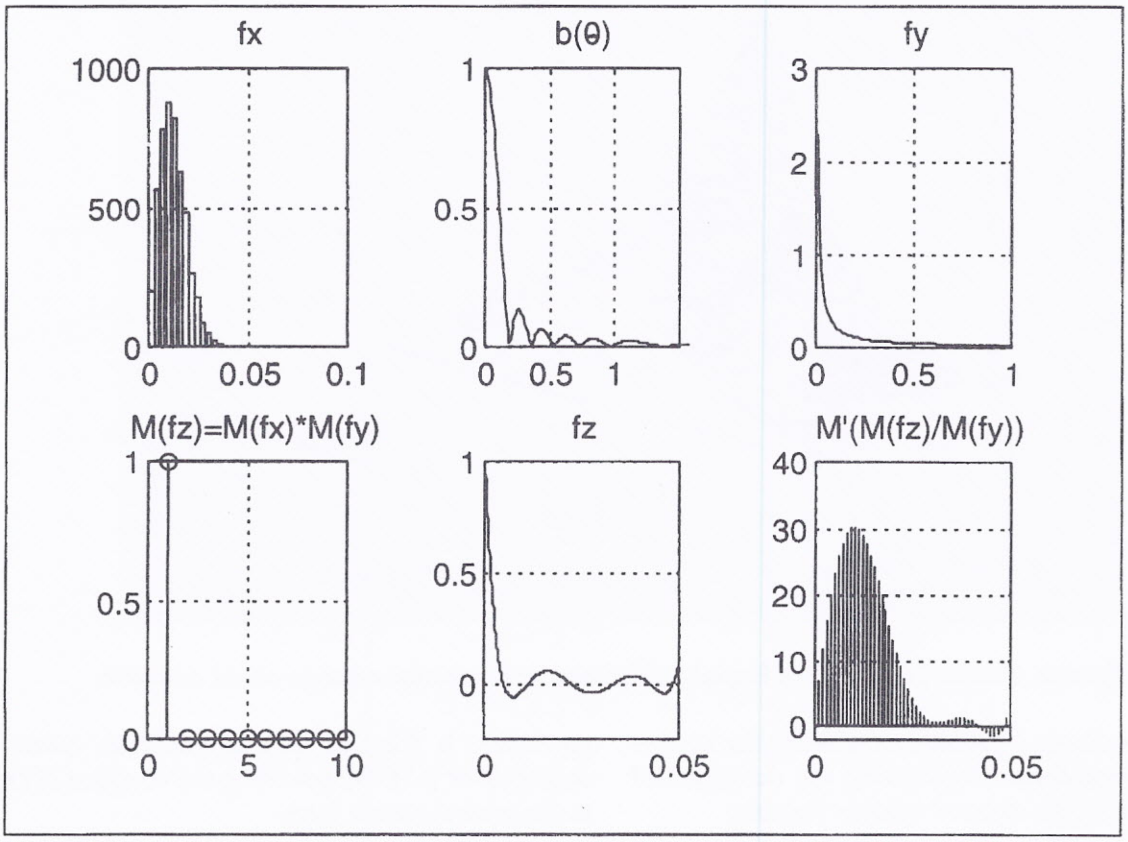

Figure 2 . Reconstruction of the PDF from a Rayleigh random variable using the Discrete Mellin Transform and SVD with a matrix pseudo-inversion.

3.2. EXPECTATION, MAXIMIZATION AND SMOOTHING (EMS)

Expectation-Maximization-smoothing is a modification of the EM method [25] which smoothes or filters highly variable estimates from what should otherwise be a smooth result. It is applied for the first time to estimate the scaled PDF of the „on-axis" voltages, $f_s(s)$ in equation (1) from which fish target strength is determined. In addition, the EMS method constrains estimates to be positive and reduces the time needed to converge by smoothing groups of estimates per iteration.

To apply EMS method the „single-target" integral equation (1) is transformed to a convolution:

$$f_V(v) = \int f_B(x)\, f_S(y-x)\, dx \qquad (16)$$

where $v = v_{max}\, e^{-y}$ $(y = \ln v_{max} - \ln v)$, v_{max} somewhat larger than the largest measured v, $b = e^{-x}$ $(x = -\ln b)$, $dx = -1/b\, dB$

We introduce a scalar ξ to account for the physical reality of an abundance of targets, as we did in the EMS methodology [25]:

$$\xi f_V(v) = \int f_B(x)\, \xi\, f_S(y-x)\, dx \qquad (17)$$

The integral can be approximated by the convolution sum to numerically obtain the solution :

$$\xi f_V(j) = \sum f_B(i)\, \xi\, f_S(j-i)\, \Delta x \qquad (18)$$

where the indices i and j correspond to bins in *X* and *Y* space respectively.

The equation (18) can be interpreted as a linear equation and can be presented in a matrix form:

$$y = \boldsymbol{K}x$$

where:
K - kernel matrix of equation,
y - observed data,
x - unknown function.

Every iteration procedure performed during solution when using EMS method consists of three steps: called respectively: expectation, maximization and smoothing.

First step - estimates the statistics of y(x) as a conditional expectation:

$$y^{(n)} = E\left(y \middle| \sum_{i=1}^{N} y_{ij}, x_{ij}^{(n)}\right) \tag{19}$$

where $^{(n)}$ denotes n-th iteration.

Second step - takes the estimated data to calculate maximum likelihood estimates as a solution of the following equation:

$$E\left(y_{ij} \middle| x\right) = y^{(n)} \tag{20}$$

The last step in every iteration - smoothes solution x using Gaussian kernel with locally weighted end points. The smooting process centers the kernel at each data point :

$$x^{(n')} = \sum_{j} S_{ij} x^{(n)} \tag{21}$$

where S - smoothing matrix.
Finally, assuming Poisson PDF of random variable related to observable y we received equation describing first two steps in a form [12]:

$$x^{(n)} = \frac{x^{(n-1)}}{\sum_{i} K_{ij}} \left(\frac{y^{t}}{x^{(n-1)} K^{T}} K \right) \tag{22}$$

3.3. REGULARIZATION METHOD

Linear inverse problems can be treated as a reconstruction of an unknown function *f(.)* *(target strength PDF)* out of the observed function *y(.) (echo PDF)*. Thus, the single-target integral equation can be presented in the form of a linear operator equation:

$$y(u) = (K\,f)(u) + n(u) \tag{23}$$

where:
K is the linear operator,
n represents stochastic or deterministic noise.

One way to solve this problem is to apply square regularization introduced simultaneously in 1962 by Tichonow, Phillips and Twomey [30]. According to this method the solution estimate can be obtained as [30]:

$$\hat{f}_{\lambda} = (K^{*} K + \lambda I)^{-1} K^{*} y \tag{24}$$

where I is the identity matrix.

Alternatively one can use iterative back-projection [29]:

$$\begin{aligned} \hat{f}_0 &= \mu K^{*} y \\ \hat{f}_1 &= \hat{f}_0 + \mu K^{*}(y - K\hat{f}_0) \\ &\;\;\ldots \\ \hat{f}_{m+1} &= \hat{f}_m + \mu K^{*}(y - K\hat{f}_m) \end{aligned} \tag{25}$$

where λ and μ are regularization parameters.
What needs to be observed is that computation of the presented iterative sequence does not require matrixes to be inverted which in ill conditioned cases constitutes a major problem. The key issue here is an optimal selection of regularization parameters in both methods.

A variation of this method which introduces a tri-diagonal matrix as a λI stabilizer was used in the experimental part of this paper. The advantage of this modification is the possibility of an additional *regulation* of the solution's behavior in boundary areas. The solution for the considered case is obtained as follows..

Regularization of the convolution integral equation of the first kind (in TS domain)

$$f_z(z) = \int_{-\infty}^{z} f_x(x) f_y(z-x)\,dx$$

is to reach the second kind equation by adding to the right hand side of the so called regulator that depends on the parameter λ and the unknown function f_x and its derivative. Introducing a functional that determines the error in space L_2 one should determine $f_x(x)$ by minimizing this functional that leads to Euler's equation.
The solution of this equation can be determined by substituting the integration with discrete summation and obtaining the following equation:

$$K^{*} K f_x - K^{*} f_z = \lambda\, C f_x \tag{26}$$

where K is the matrix of the transformation kernel formed from the convolution vector f_y,
K^{*} conjugate matrix,

C stabilizer matrix in the form:

$$\begin{bmatrix} c_{11} & c_{12} & & & \mathbf{0} \\ c_{21} & c_{22} & c_{23} & & \\ & c_{32} & \ddots & \ddots & \\ & & \ddots & \ddots & \ddots \\ \mathbf{0} & & & \ddots & c_{nn} \end{bmatrix} \qquad (27)$$

where:

$$c_{i,i} = 1 + \frac{2}{h^2}, i = 2..n-1, h = 1 - sampling\, step;$$

$$c_{i,i-1} = c_{i-1,i} = -\frac{1}{h^2}, i = 2..n$$

$$c_{11} = c_{nn} = 1 + \frac{k}{h^2}, k = \begin{cases} 1 \text{ for } f_x'(0) = f_x'(n) = 0, \\ 2 \text{ for } f_x(0) = f_x(n) \end{cases}$$

The matrix of stabilizer C is a tri-diagonal matrix because when computing the derivative the difference version was used which gives the relation between the following, current and previous index in vector f_x. At the same time boundary conditions define the value of the first and last element of the main diagonal.

In the context of target strength the estimate of PDF can be written down in the matrix form:

$$\hat{\mathbf{p}}_{TS} = (\mathbf{P}_B^*\mathbf{P}_B + \lambda\, \mathbf{C})^{-1}\mathbf{P}_B^*\mathbf{p}_E \qquad (28)$$

where:

$\hat{\mathbf{p}}_{TS}$ vector of the estimate of target strength PDF

Pe matrix of echo PDF

Pe' transpose of a matrix Pe

λ - regularization parameter

C matrix of regularization stabilizer

$\mathbf{p}_E$ vector of echo distribution

3.4. DECONVOLUTION USING SINGULAR VALUE DECOMPOSITION

Singular value decomposition (SVD) has become a standard method of solving ill conditioned linear equations. Extensive description of the problems related to the SVD theory is related to spectral analysis [17]. Below we used only parts of the theory that can be applied to the solution of inverse problems. Let $\|\cdot\|_2$ represent a norm in space L_2 and $[,]$ represent a scalar product. If K^*K is a linear operator, then $(e_v(t))$ represents its eigen functions, k_v^2 singular values and $h_v(u)$ a normalized transform

$h_v(u) = (Ke_v)(u) / \|Ke_v\|$.

If none of the singular values is a zero value then the reconstruction formula has the following form:

$$\hat{f} = \sum_v k_v^{-1}[Kf, h_v]e_v \qquad (29)$$

In the case when singular values of the K^*K operator approximate zero, it is necessary to introduce weights so that dividing by elements close to zero does not impact the stability of the solution. By adequate introductions of the weights, we obtain the so called WSVD (Windowed SVD) which gives the reconstruction rule:

$$\hat{f}_w = \sum_v w_v k_v^{-1}[y, h_v]e_v \qquad (30)$$

As an example, the simplest selection of weights is to assume $w_v = 1$ for small indexes ν and $w_v = 0$ for large ν which reflects the name assigned to this method. Other approaches are possible as well [1]. What is also worth noticing is that if we select $w_v = k_v^2 / (k_v^2 + \lambda)$, then we obtain the regularization method presented in the previous paragraph in the direct form and when $w_v = (1 - (1 - \mu k_v^2)^m)$ we obtain the method of iterative reconstruction (m-number of iteration). By using the form of the Penrose-Moore pseudo-inverse matrix $\mathbf{A}^{\#}$ as an inverse matrix obtained in the SVD technique, we obtain a formula for target strength PDF estimate:

$$\hat{\mathbf{p}}_{TS} = \mathbf{P}_B^{\#}\mathbf{p}_E \qquad (31)$$

4. COMPARISON OF TS-ESTIMATION METHODS

Comparison of the results (TS histograms) obtained from the analyzed estimation methods is presented in Fig. 3. Data were acquired from acoustic surveys

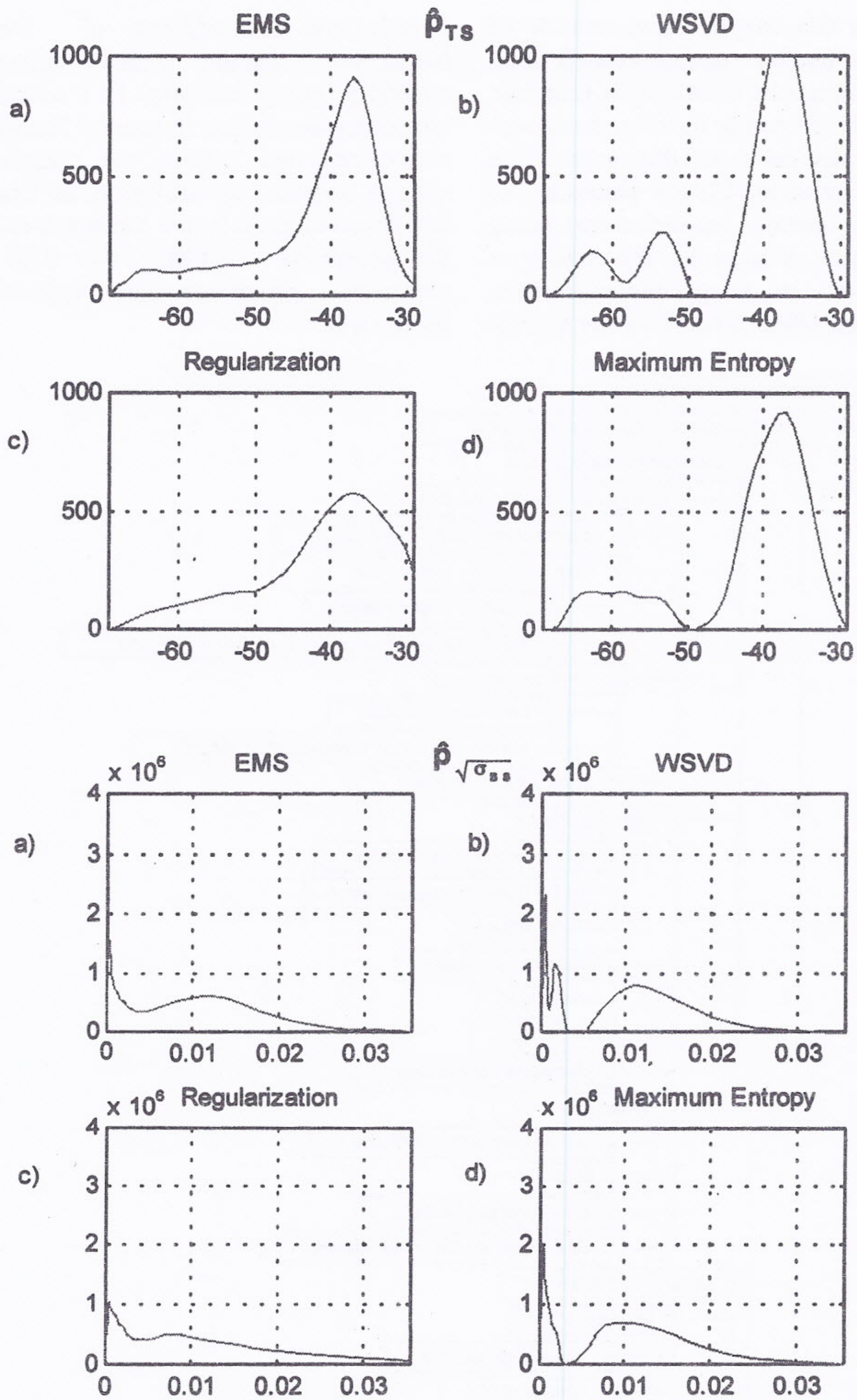

Figure 3. Comparison of various target strength PDF estimation methods in logarithmic domain (upper part) and in absolute variable domain (lower part)

on salmon populations in Lake Washighton. As it is easily seen the EMS and Maximum Entropy Regularization methods give smoothed estimates (by iterations). WSVD produces artifactual modes, but on the other hand it gives much faster numerical solution.

To conclude this chapter some revision of target strength estimation methods classification schemes as introduced by Foote [9] is proposed in order to include the newly developed state-of-the-art methods discussed in this paper. The primary changes refer to: (1) the placement of MER (maximum entropy regularization) along with EMS method, labeled by the author as *iterative methods* in a logarithmic domain, (2) addition of the DMT method to the voltage domain and (3) addition of the WSVD (windowed singular value decomposition) method to matrix inversion as a subclass. Other minor changes follow in general Hedgepeth [12] suggestions and include the addition of the voltage domain, the inclusion of Craig-Forbes and deconvolution in the same sub-section, and the possibility of fitting the Rice PDF in parametric estimation (as opposed to *a posteriori*):

- A.Indirect insitu methods
  - 1. Single-target statistical approaches
    - a. Non-parametric statistics
      - i. logarithmic domain (and dB)
        - a. deconvolution and Craig-Forbes
        - b. matrix inversion techniques
          - i. Tichonov Regularization
          - ii. WSVD (weighted singular value decomposition)
        - a. iterative techniques
          - iii. EMS deconvolution
          - iv. Maximum Entropy Regularization (MER)
        - d. piecewise polynomials
      - ii. intensity domain
        - a. matrix inversion techniques
          - i. Tichonov regularization
          - ii. WSVD
        - b. iterative techniques
          - i. EMS
          - ii. MER
        - c. piecewise polynomials
      - v. voltage domain
        - a. matrix inversion techniques
        - b. EMS
        - c. piecewise polynomials
        - d. DMT (discrete Mellin transform)
    - b. parametric statistics
      - i. Rayleigh PDF
        - a. Incomplete gamma
        - b. least squares
      - ii. Rice PDF
        - a. least squares
      - iii. polynomial (i.e. cubic)
        - a. least squares
    - c. simultaneous echo counting and integration

Table 1. Revised classification scheme of target strength estimation methods

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