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Bathymetry Data Processing using Adaptive Filtering and Validation on Indian Reservoirs.

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Abstract:*Reservoirs are the lifeline of India and it economy depends on irrigation and agriculture. Sedimentation process erodes the agricultural land as well as fills the storage capacity of the reservoirs. Proper estimation of the reservoir capacity depends on the accuracy of depth measurement which depends on the echo sounder output. However most of the data collected from Indian lake are affected by various noises due to submerged vegetation, nature of sediment, under water and mechanical noises. This paper analyses the depth data collected at two different lakesusing adaptive filters and geo statistical interpolation techniques. The objective is to evaluate most accurate volume of the lakes by selecting appropriate filters/ interpolation technique. The performance of the filters was evaluated based on a simulated signal and optimized. The validation was carried out with the original data as well as from the measured dredged volume. An optimal filter/interpolation was identified for smooth and rough bed reservoirs. A common approach based on the studies for different type of Indian lakes is derived from the studies.*

Keywords: *Adaptive filtering, Bathymetry data, Data Interpolation, Sedimentation.*

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I. Introduction

India as a whole is severely affected by water related issues both heavy rainfall and lots of erosion; and reduced water storage due to heavy sedimentation during the recent years. Bathymetry survey is the only direct measurement method used to estimate the capacity of the live and original storage capacity. This data analysis provides the shape of the bed floor features. To accept the bathymetry and to characterize the nature of the reservoir bed, studies of echo signal waveforms and their parameters such as backscatter signal strength is to be analysed [1]. Finding the depth of the reservoir using acoustic wave is affected by the accumulation of sediments and submerged trees, hard rocks and aquatic vegetation. During the actual bathymetry surveys large numbers of spikes are generated due to the submerged object which gets added to the data when the survey boat moves over nonlinear profiles such as submerged trees and hard rocks[2]. All commercial softwareremoves spikes, but not representing the true bed.

In an experiment to estimate the accuracy of depth, RESON 420 dual frequency echo sounder was used in a laboratory setup. The experiment was carried out in a test tank of 2mX 1.5mX 1.5m with of different sedimentary rocks and walnut powder [3].The result shows at least 10% variation between the actual and measured depth when the power, frequency and beam angle of the echo sounder are altered. This is because the underwater sound propagates as rays which are reflected by the surface and several layers of sediments in the bottom of the reservoir in addition to the direct path. The reflected ray is mathematically represented as an output of FIR filter with an impulse response [4],

$$h(t) = \sum_{i=1}^{k} a_i \delta(t - \tau_i), \quad a_i, \tau_i \in \mathrm{R} \qquad \text{Eq. (1)}$$

where a_i is the attenuation factor, τ_i is the time delay of the i^{th} path, K is the number of path and δ is the delta function.

For a wideband signal *e (t)*, the received signal is given by;

$$r(t) = s(t) + n(t), \; where \; s(t) = \sum_{i=1}^{k} a_i e(t - \tau_i) \qquad \text{Eq. (2)}$$

s (t) is the noise free signal while n (t) is the noise.

In this work, we deal with removal of underwater noises which are present in the bathymetry data collected using a dual frequency echo sounder with the reflection taking place from the nonlinear surfaces. A. Jarrot [5] studied the analysis of underwater noise and based on the Power Spectrum Density (PSD), considered the noise as non-white. It is assumed that the underwater noise is additive, Gaussian, stationary. However, the sediment type, submerged trees and aquatic ecology, affect the echo quality and its speed with non-Gaussian noise in form of spikes inside the lake[6].

In many previous analysis [7][8], noise removal was considered in the pre-processing stage before interpolation. However, filtering data in pre-processing stage will smoothen out the actual profile, since the bathymetry survey is done at different geographical location which is two dimensional and each data is dependent on its neighborhood points.

II. Approach

Two different noisy data are used to examine the efficiency of the filters for de-noising of signals. The first type is synthetic data. The second type is the actual bathymetry data. For the first approach based on the literature reviews, a noise free bathymetry data $s(m)$is considered which is modelled with noise $n(m)$at different levels of noise, where$m$ correspond to the no of samples. Both $s(m)$and $n(m)$ dataset is subjected to data mapping grid with different interpolation techniques to generate values which are not present to obtain a complete map. In the second approach, bathymetry data obtained from survey of two different lakes which are geographically apart with different sediment characteristics. During data interpolation, the data is extrapolated outside the data range. To curb this, boundary is extracted from the field with GPS, which is a superimposed onto the interpolated data and area of interest is extracted.

Evaluation of comparative suitability of these techniques applied over the same data sources is imperative as it may result in different results depending on data distribution, propagation and contextual properties[9]. Finding a reliable interpolation scheme is a great challenge as most of them do not provide any estimation of interpolation noise. Prominent interpolation schemes include Kriging, Inverse Distance Weighted, Radial basis function Natural neighbor, nearest neighbor, Minimum curvature, Modified Shepard's, Triangulated Linear interpolation are studied.

Kriging is a geo statistical method based on regression against observed values of surrounding data points, weighted according to spatial covariance values[10]. The *Inverse Distance Weighted (IDW)* approach calculates the value as a distance-weighted average of sampled points in a defined neighborhood. *Radial basis function* methods are based on the assumption that the interpolation function should pass the data points, and at the same time, should be as smooth as possible RBFs minimize the total curvature of the surface[11].*Natural neighbour* is a weighted-average interpolation method which creates a Delaunay triangulation of input points and selects the closest node that form a convex hull around the interpolation point[12]. *Nearest neighbor* interpolation technique assigns the value of the points whose centre is closest to the centre of the output cell for discrete, or categorical, raster data, such as surface mesh, because it does not change the value of the input cells [12]. *Minimum curvature* technique involves the fitting of traditional interpolation two-dimensional splines to the observed data. Spline interpolates a surface from points using a minimum curvature spline technique[9]. *The Modified Shepard's Method* uses an inverse distance weighted least squares method, similar to the Inverse Distance to a Power interpolator, but the use of local least squares [12]. *Triangulation with linear interpolation* creates triangles by drawing lines between data points. The original points are connected in such a way that no triangle edges are intersected by other triangles. The result is a patchwork of triangular faces over the extent of the grid [12].

Modeled gridded surface data will provide a meticulous analysis in noise reduction. After data mapping, the performance analysis of interpolation methods is done for both noise free gridded data $Z(x, y)$ and noisy data $\hat{Z}(x, y)$ by calculating the deviations of interpolated depth values from corresponding actual values in terms of root mean square error (RMSE). This will provide measure which interpolation method has improved the modelled noisy data with the actual data. The obtained result after interpolation, following adaptive filters (de-noising techniques) are applied.

2.1 Adaptive Filtering

There has been a significant development in the field of adaptive filtering in recent years. Generic FIR and IIR filters are based on a priori design which are fixed. These filters cannot respond to changes that might occur during the course of the signal. Adaptive filters have the capability of modifying their properties based on selected features of signal being analyzed [13]

a. Two Dimensional Least Mean Squares(TDLMS)

The simplicity and relatively fewer computational operations makes Least Mean Square (LMS) a favorable approach in approximation of unknown signal [14]. In TDLMS, the next weight matrix is equal to the present weight matrix plus the change proportional to the negative gradient[15].

$$W_{j+1} = W_j - \mu G_j \qquad \text{Eq. (3)}$$

Where, W_j is the weight matrix before updating, W_{j+1} is the weight matrix after updating, μ is the Scalar multiplier controlling the rate of convergence and filter stability, G_j is the estimate for the 2-D instantaneous gradient of $E[e_j{}^2]$ w.r.t. W_j. $G_j = \frac{\partial E[e_j{}^2]}{\partial W_j}$

Weight matrix size= 5; Step size= $5x10^{-8}$

b. Adaptive Wiener Filter (AWF)

Wiener filter is one of the prominent method used in image restoration by reducing mean square error between the original and processed signal [16]. Adaptive filtering was evolved since the signal characteristics differ considerably from one region to another. Local variance of noise free signal is determined from degraded signal and prior knowledge. A designed space variant filter is then applied to the degraded signal in the local region. Given a uniform moving average window weight function $w()$, the local mean and variance is estimated adaptively as given,

$$\breve{\mu}_x(i,j) = \sum_{p=i-r}^{i+r} \sum_{q=j-r}^{j+r} w(i,j,p,q)\, y(p,q) \qquad \text{Eq. (4)}$$

$$\breve{\sigma}_x^2(i,j) = \sum_{p=i-r}^{i+r} \sum_{q=j-r}^{j+r} w(i,j,p,q)[y(p,q) - \breve{\mu}_x(i,j)]^2 \qquad \text{Eq. (5)}$$

Where $y(i,j)$ is the noise measurement $y(i,j) = x(i,j) + n(i,j)$,$x(i,j)$ is the additive noise free mesh and $n(i,j)$is the additive Gaussian noise. Weight matrix size=5.

c. Adaptive Savitzky Golay Filter (ASGF)

Savitzky and Golay [17]proposed a method of data smoothing based on local least-squares polynomial approximation. The main advantage of the Savitzky Golay filter (SGF) is its ability to preserve the signal compared to other methods of filtering. SGF are designed for various applications in the field of Synthetic Aperture Radar (SAR) , underwater acoustic signal processing [8]and biomedical signal processing[18][19]. In all of these applications SGSF is used as de-noising and smoothing tool without destroying their fundamental properties.

If x is noisy signal with noisy samplesx_m, n = 0, 1… L-1and noise is reduced to obtain a smoothed output version y which containsy_n, then input vector has n =L input points and $x = [x_0, x_1, \dots, x_{L-1}]^T$is replaced by N dimensional one, having M points on each side of x.

$$x = [x_{-M}, \dots, x_{-1}, x_0, x_1, \dots, x_M]^T \qquad \text{Eq. (6)}$$

The Smoothed output y is calculated as $y = Bx$

The SGF coefficients $b_0, b_1, \dots, b_n$ are the elements of matrix B.

$$B = [b_{-M}, \dots, b_{-1}, b_0, b_1, \dots, b_M]^T \qquad \text{Eq. (7)}$$

$B = GS^T$, where $G = S(SS)$

$$S = [s_0, s_1, \dots, s_d], s_0(m) = 1;\ s_1(m) = m;\ s_2(m) = m^2 \qquad \text{Eq. (8)}$$

$where - d \leq m \leq d$

The order and frame size is chosen optimally using Stein's unbiased risk estimate (SURE) [20]. The order is varied from 1 to 10 and semi window length of 3 to 30.

III. Implementation and Evaluation Results.

As discussed earlier, the implementation is done on two different types of noisy data- Artificial noisy data and original bathymetry data. The performance evaluation is also done for the interpolation methods using RMSE (Root Mean Square Error) as the criteria. The denoising performance of the filters are judged by the value MSE (Mean-Square-Error) and PSNR (Peak Signa1-to-Noise Ratio), which aredescribed in Equation (6) and Equation (7). For MSE or PSNR to be taken as estimator, the original noise-free signal is need to be known**.** However, it is difficult to get original noise-free signal in actual. Hence, when noise-free signal cannot be obtained, the autocorrelation coefficient $\boldsymbol{r}$ for the de-noised signal is chosen as an estimator to judge the performance of de-noising. The larger autocorrelation coefficient represents it has better performance. And the autocorrelation coefficient $\boldsymbol{r}$is defined in Equation (8). All data processing was performed off-line using MATLAB software package while the data interpolation and gridding is done using SURFER 8 software.

$$MSE = \frac{1}{L} \sum_{i=0}^{L-1} [X(i) - Y(i)]^2 \qquad \text{Eq. (9)}$$

$$\text{PSNR} = 10\log_{10}\frac{L^2}{MSE} \quad \text{Eq. (10)}$$

where $X(i)$ is the noise-free original data, $Y(i)$ is the predicted filtered data and L is the length of the data.

$$r = \sum_{i=0}^{L-1-m} \hat{y}(i)\hat{y}(i+m) \quad \text{Eq. (11)}$$

where $\hat{y}$ is the reconstructed signal, L is the length of the signal and m is the lags.

Table 1: PSNR for different de-noising techniques (Synthetic signal)

Filter performance in terms of PSNR(dB) at various noise levels (dB)									
Interpolation methods	**10 dB**			**20 dB**			**30 dB**		
	TDLMS	**AWF**	**ASGF**	**TDLMS**	**AWF**	**ASGF**	**TDLMS**	**AWF**	**ASGF**
Inverse Distance	39.83	40.27	41.85	38.72	40.46	43.08	38.96	40.71	44.05
Kriging	38.75	40.24	41.72	39.87	43.07	44.20	40..83	47.00	47.91
Min Curvature	38.49	40.28	41.13	38.29	41.25	42.16	39.402	43.58	44.59
Natural neighbor	35.03	36.25	40.10	39.97	42.97	44.28	40.78	46.13	46.96
Nearest neighbor	38.92	40.72	41.33	38.62	40.72	41.33	39.62	42.78	44.70
Radial Basis	37.94	40.38	41.18	38.16	39.95	42.02	39.99	43.17	45.31
Modified Shepard's	26.69	27.34	28.97	30.60	36.63	38.16	34.76	38.02	41.63
Triangulation Linear	38.92	40.20	41.34	39.41	41.64	43.08	40.52	44.62	46.23

a. For synthetic data.

Simulation in done using synthetic signal obtained from MATLAB test matrix consisting arbitrary data from standard uniform distribution using function *gallery ('uniform')* [21]. Total no of samples considered is 500. The synthetic signal is basically exponential function given by

$$v = x * e^{(-x^2-y^2)} \quad \text{Eq. (12)}$$

Where x and y are of uniform distribution.

Additive Gaussian noise is introduced to the signal with SNR of 10dB, 20dB, 30dB. Both clean synthetic signal and noisy synthetic signal are subjected to interpolation. The modeled gridded surface data will provide a meticulous analysis in noise reduction. Interpolation methods are analyzed based on the RMSE.

From Figure 1, it is evident that the RMSE is minimum for Inverse distance method compared for other methods. Modified shepard method found out to be less suitable method to analyse which is not due to a feature of the data but rather an artifact from the interpolation algorithm [22]. On the analysis of filters, Table 1indicates that based on PSNR, the de-noising performance for ASGF is more signifanct expecially at low SNR value.

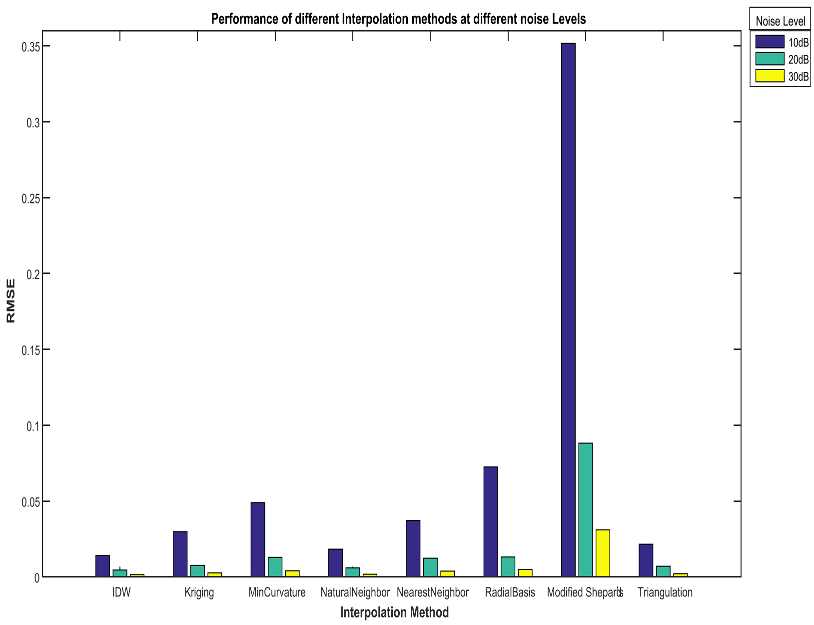

Figure 1: RMSE for different interpolation methods at noise levels of 10dB, 20dB and 30Db

a. For actual bathymetry data.

In this experiment, the bathymetry data was obtained using same echo sounder operating at 33khz with 1 W power from two different reservoirs in India; one in the Western Ghats with fairly smooth bed and another lake in river Narmada with submerged trees and hard rocks, are considered. The following equipment was used in the data collection: SYQWEST echo sounder, SOKKIA RTK-GPS devices along with NAVISOFT and HYPACK software packages. The position accuracy is ensured within centimeter level accuracyusing RTK-GPS. Similarly depth was acquired with 5cms accuracy underwater with echo sensor and 1 cm with RTK GPS in land survey. The smoother lake had 26855 data samples, while the rougher surface lake had 12872 data samples and both have a grid interval of 1m. For analysis, a 100m x 100m surface is used for both the lakes.

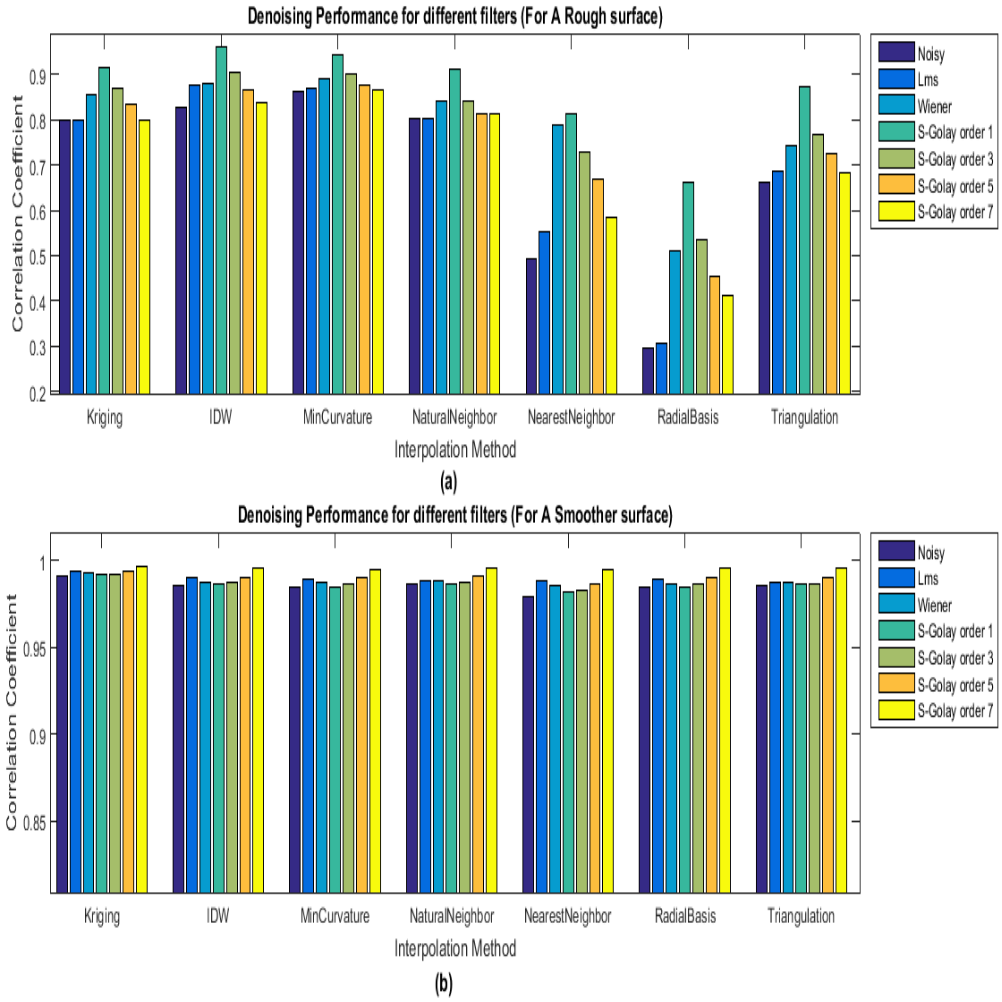

Figure 2 Denoising performance by autocorrelation coefficient for different filter (a) For Rough surface (b) For Smooth surface.

Since, the noise-free bathymetry data is unknown, autocorrelation coefficients are taken as an estimator. Three different methods are used for de-noising the bathymetry data. The results illustrate in Figure 2 (a) and Figure 2 (b). The higher value of the coefficients means the less noise remain in the signal after de-noising processing. On correlation analysis on both the cases, the performances of the filter weredepending due to different noisy conditions. In case of rough bed lake, the 1st order S-Golay filter performed better compared higher orders, and AWF had better correlation factor than TDLMS filter. While in case of smooth profile lake, higher order filter had better a denoising performance; and among AWF and TDLMS Filter, TDLMS filter fared better. The result indicates that the order of filter proportionally increases to the bed surface roughness.

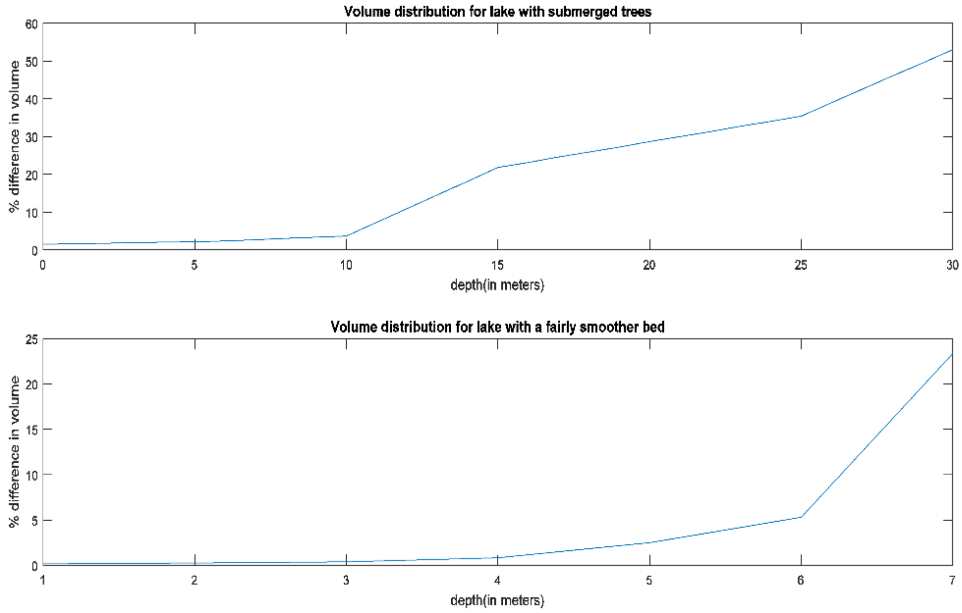

Figure 3 Denoising evaluation on volume difference: Volume vs Elevation graph for the two lakes

In thevolume analysis of the bathymetry data, the calculation was inefficacious due to the presence of noise. Volume estimation is done by Trapezoidal and Simpsons rule. The ASGF produced a considerable difference in volume of the order of 23% in smooth bed reservoir and 53% for the rough bed reservoir (Figure 3). For evaluation purposes only a small portion of approximately one sq. km of the lake data was used in this study. The volume calculated was compared with the pre and post dredged volume in the lake at western ghats with the smoother bed.

IV. Conclusion

The analysis of the underwaterdepth data is carried out considering the different interpolation and de-noising methods. While evaluating the interpolation algorithm with RMSE as test criteria, Modified shepard method fails to analyse in both reservoir conditions, which is due an artifact from the interpolation algorithm. Excluding this method, the filter performances are assessed on the remaining interpolation algorithms by MSE and PSNR sense. The main advantage of these adaptivefilters are that the filter parametersare tuned to the test statistical criteria such as MSE and SURE. On the synthetic data, all the filtering methods were evaluated and ASGF has found to have better performance over other adaptive filters with an improvement of atleast 1dB. The smoothning algorithm applied on the reservoir data, with the grid size of 100m x 100m size, demonstrates that the ASGF proved to show 0.93 corelation coefficent for rough bed surface and 0.99 corelation for smoother surface. The volume calculations obtained with the filter performance was validated with the dredged volume which is accurate to 99 percent.

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