KALMAN FILTERING FOR 3^D REAL TIME DATA VISUALIZATION OF MULTIBEAM SONAR RECORDS

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For the last decade multibeam sonars have been increasingly used for mapping and visualization of the bottom surfaces to provide the 'physical bases' for environmental studies due to theirs unprecedentedly high resolution mapping ability. However, the raw sonar records are subject to systematic errors, random noise and outliers. In this paper Kalman filtering approach to generating optimal estimates of bottom surface from a noisy raw sonar records is presented. The experiment on the surface indicates that after applying the Kalman filtering technique the outliers of raw records can be effciently detected and removed. Moreover in the same time, the two-step Kalman filtering method is applied, which aims to filter every multibeam sonar swath and enable 3^D seabed visualization in real time. The 3^D bottom relief before, and after the filtering method application is also presented.

INTRODUCTION

As computer and multibeam sonar has become central to the high-definition bottom mapping, 3^D imaging of seabeds has become very attractive in that area. Increasing amount of digital (raster) and very precise echo records from multibeam sonar have enhanced the potential of computer modeling of the marine environment to improve our understanding of the bottom processes.

The bottom area data mapped with multibeam sonar usually contain bathymetry data along with navigational information (e.g. UTM coordinates), allowing for further visualization

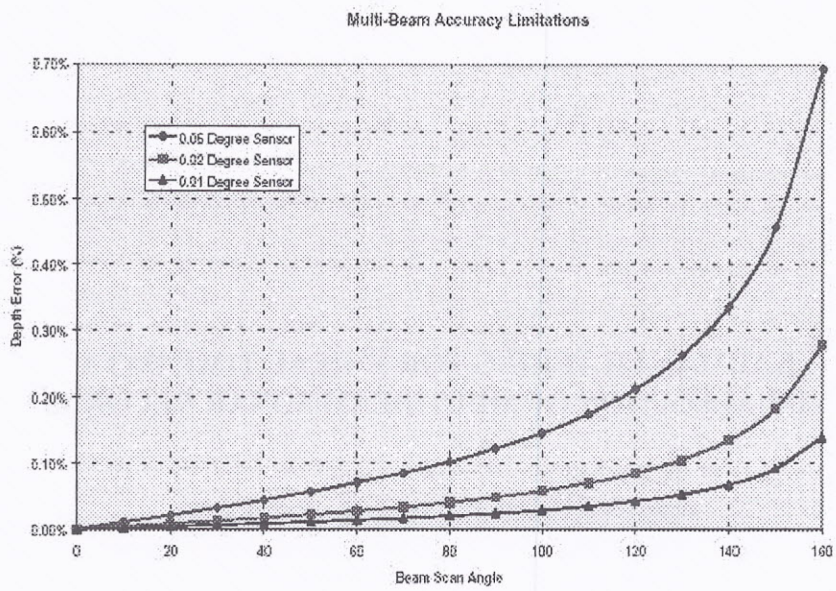

Figure 1: Multibeam sonar accuracy, from [1].

and mapping of a geographically defined area. However, a raw echo records from multibeam sonar are analyzed and visualized rather rarely as are typically interfered by many sources of noise, spikes and outliers, which affects the quality of representation of contours and slope of bottom lines.

The noise sources may be breaking waves, rain, thermal, seismic activity, ships, animals, and so on. This is so called *an ambient noise*. However the error sources of a great importance is heading, either determined from gyro or GPS phase measurements between the two GPS carrier phase receivers, velocity and position from GPS together with roll, pitch, heading (yaw) of a ship and acceleration measurements, which are also an input into the Kalman filter. As turns out the data provided by peripheral units play the crucial role in the precise positioning and application of correctors to the multibeam sonar bottom relief mapping. The error in depth is a function of several parameters. Roll errors is more significant then errors in pitch. The error is especially important for greater beam angels [1] as was shown in the Fig. 1. A sample 3^D visualization of the noisy multibeam data is presented in the Fig. 2. For the relatively slow dynamic of the measured signal, as a bottom depth is in fact, very dense raster measurements from the multibeam sonar perfectly fit the digital Kalman filter algorithm.

1. KALMAN FILTER THEORY

The Kalman filtering technique was firstly introduced in 1960. A typical Kalman filter application are navigation systems, as well the motion objects tracking, obstacles detections. Usually, the inputs of the filter are a current position measured in regular time intervals, in terms of the Kalman filter terminology known as an innovation [2]. The outputs of the filter is a position and velocity of the objects in the three dimensional system (i.e. Cartesian system). An important concept of Kalman filtering is the 'state'. The state of a system is defined as the minimum information about the past and present, needed to determine all future responses of a system given the future input [3]. In a certain random case, it can be considered as the minimum amount of information about past and present estimates, needed to determine an optimal casual estimate of future responses, given future noisy observations. The concept of state actually forms the stochastic difference equations, i.e. dynamic model, as follows:

$$S^{-}(i) = A(i)S^{+}(i) \tag{1}$$

$$P^{-}(i) = A(i)P^{+}(i) + Q(i) \tag{2}$$

$$K(i) = \frac{P^{-}(i)H^{T}(i)}{H(i)P^{-}(i)H^{T}(i) + R(i)} \tag{3}$$

$$S^{+}(i) = S^{-}(i) + K(i)[Z(i) - H(i)S^{-}(i)] \tag{4}$$

$$P^{+}(i) = [I - K(i)H(i)]P^{-}(i) \tag{5}$$

where $S^{-}(i)$ is the predict estimate of state vector, $P^{-}(i)$ covariance matrix associated with $S^{-}(i)$, $K(i)$ Kalman gain, $S^{+}(i)$ update estimate of state vector, $P^{+}(i)$ covariance matrix associated with $S^{+}(i)$, $A(i)$ transition matrix for the state and $H(i)$ is transition matrix for the measurements, $Q(i)$ covariance of the state noise, $R(i)$ the measurement noise and $Z(i)$ the innovation. The dense and regular multibeam sonar records of bottom depth are measured in a constant time intervals of echoes. We assume that the Kalman processor computes the successive multibeam records swath data from the left to right order, as in raster scanning. The echoes have very systematic grid, but to be precise the grid should be called semi-grid. Therefore, at any processing point, we have echoes (excluding the first echoes) that precede the current record.

2. KALMAN FILTERING OF MULTIBEAM SONAR SWATH

The multibeam sonar records can be grouped in the swaths, each swath contains so called pings, single echoes, which are grouped in a very regular grid. Taking into account the very regular and systematic feature of every swath, Kalman filtering was applied to every single swath, as they come from the sonar in real time (see Fig. 3). However, according to Kalman filtering theory, the quality of the state vector will vary according to its position within the raster grid, since an estimate of the state vector is optimally derived using all available information of the processed points. While the filtering progresses, the numbers of the processed points will increase, so the state vector of the points close to the end of a processing record will be generally better than those close to the starting positions. To overcome the problem, the two-step filtering procedure was applied. By applying the suggested Kalman processor twice over the same multibeam sonar swath data with different orientations. Firstly, we apply the processor from the right to left. Then, the same process is applied in reverse, i.e. from the left to right. The output of these two processes will be a subject of further optimal calculation, which yield better

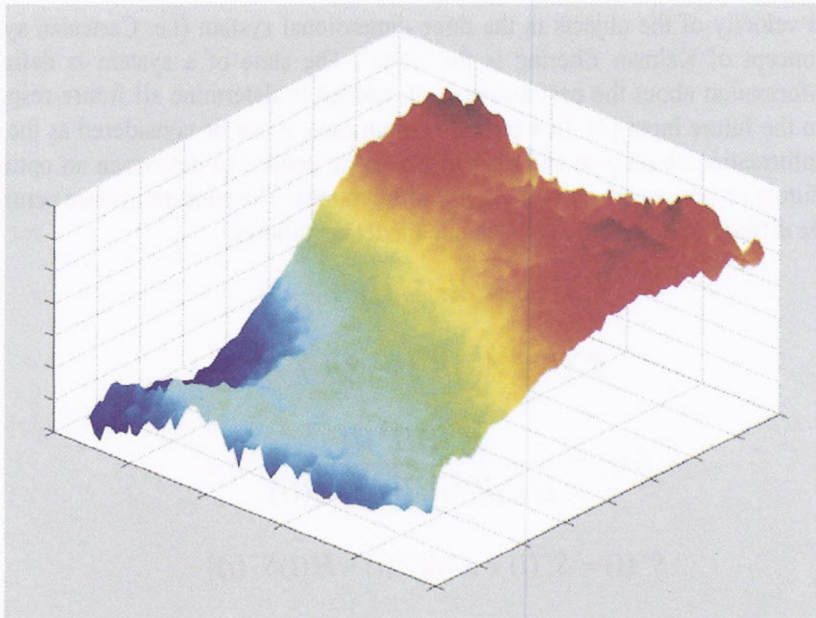

Figure 2: 3D raw echoes visualization retrieved by SeaBat 8101 multibeam sonar in Southern part of Baltic Sea.

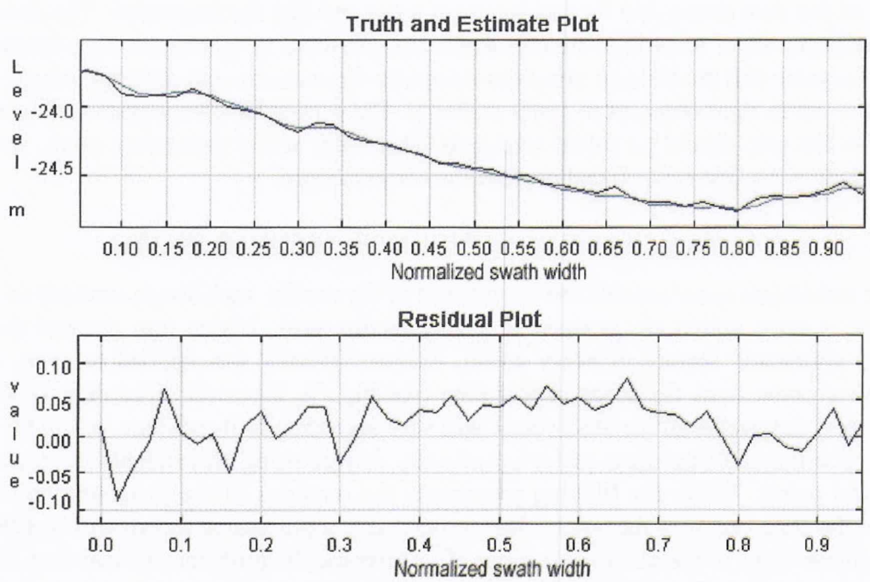

Figure 3: Kalman filter swath estimate and residual error.

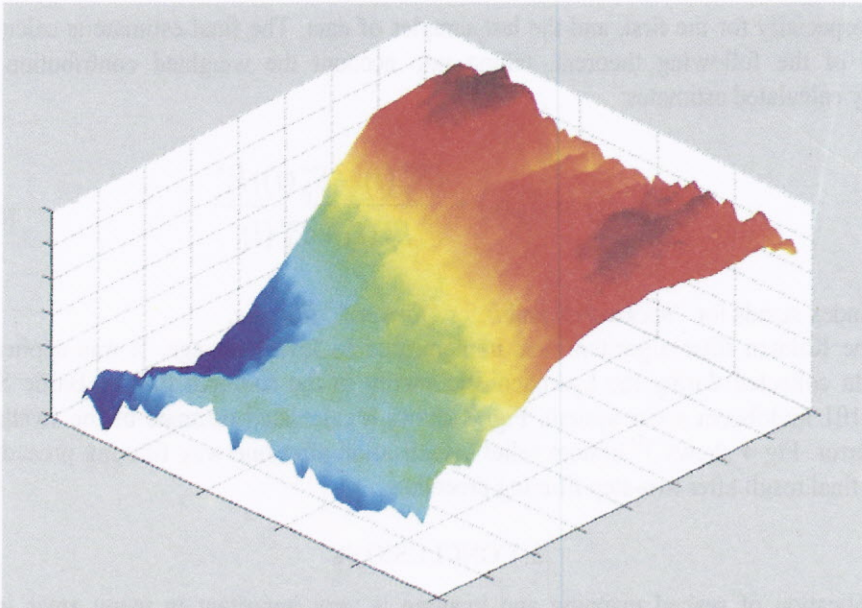

Figure 4: 3^D seabed visualization after one-step filtering procedure.

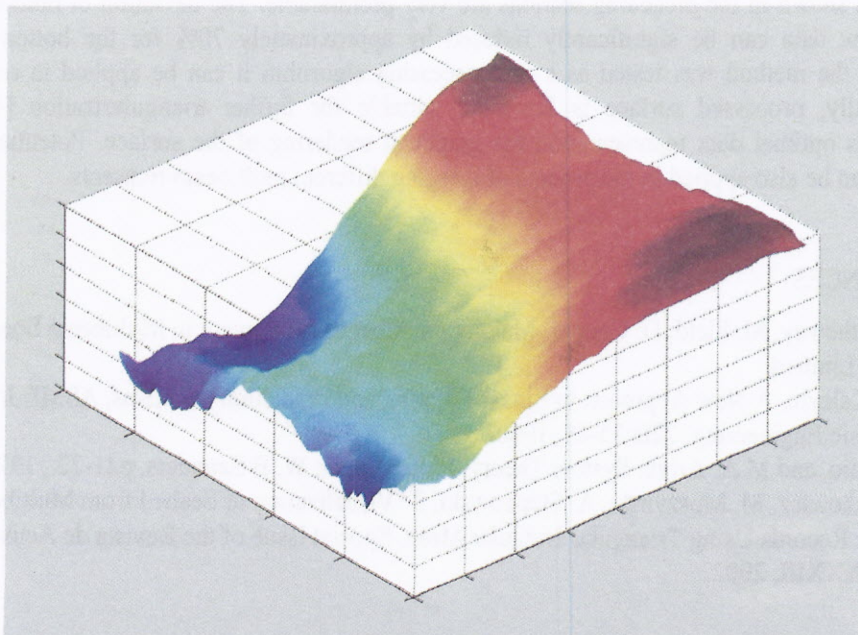

Figure 5: 3^D seabed visualization after two-step filtering procedure.

estimate especially for the first, and the last samples of data. The final estimate is calculated on the basis of the following theorem, taking into account the weighted contribution of two previously calculated estimates:

$$S_{final}(i) = S_B^+(i) + \frac{(S_F^+(i) - S_B^+(i))P_F^+}{P_F^+(i) + P_B^+(i)} \tag{6}$$

where B index stands for *"backward"* and F for *"forward"* filtering.

The Kalman filter algorithm was implemented in Java language. It was applied to the actual data collected during the hydroacoustic survey in the southern part of Baltic Sea with SeaBat 8101 multibeam sonar system. Fig. 3 shows a calculated estimate of the swath and its residual error. Fig 4 shows 3^D bottom relief visualization after one-way filtering procedure, and Fig 5 the final result after two-step filtering procedure.

3. CONCLUSIONS

Application of seabed mapping and imaging is very important in many areas including marine navigation, seafloor mapping and characterization, marine GIS, ECDIS, hydrography etc. This is especially attractive when mapping of the seabed is performed using multibeam sonar systems, which can map a bottom within the meter resolution. The article presents the result of dual way Kalman filtering applied to the multibeam sonar swath and its 3^D visualization. The results, as shown in the preceding sections are very promissable. The deviation of random noise of the raw data can be significantly reduced by approximately 70% for the bottom depth. Although the method was tested as a postprocessing algorithm it can be applied in real time. Additionally, processed surface is far more suitable for further triangularization [4] as it guarantees optimal data representation for graphical rendering of the surface. Potentially, this method can be also applied in the process of merging different multibeam transects.

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