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Application of the Digital Signal Procession in the MEMS Gyroscope De-drift

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***Abstract*—The Micro Electrics Mechanics System (MEMS) gyroscope has the virtue of lower price, smaller size, lighter weight than of the traditional rate sensors. It can be widely used in the low-price inertial navigation system. But limited by its machining precision, the MEMS gyroscope usually has the large drift. Using the digital signal procession (DSP) of drift signal, the performance of the MEMS gyroscope could be improved effectively. By a new median filtering method, the outlier signal from the drift signal was got rid of. The on-line implemented wavelet analyzing of the drift signal was used to extract the character of the gyroscope drift. A two-order AR model was built for the residual signal between the original signal and the characteristics drift signal. A group of matrix equations were built for the traditional Kalman filter. By making some improvement on these equations, an adaptive Kalman filter was used to trace the change of the residual signal adaptively and could increase the de-drift effect of the MEMS gyroscope greatly. A $50mm \times 50mm$ circuit board was made to implement the DSP. Standard variance of the dynamics signal measurement was 18.31 deg/h after the gyroscope drift was extracted.**

Keywords-micromachined gyroscope;wavelet transformation; filtering;DSP

I. INTRODUCTION

MEMS gyroscope often has the virtue of the lower price, smaller size, less weight than of the traditional rate sensor. It can be widely used in the low-price inertial navigation system. But limited by its fabrication precision, the MEMS gyroscope usually has the large drift. There are many processing methods to the drift signal, described in [1][2][3]. But these methods are not easy to be implemented in real-time on-line and have not been used widely.

The DSP of the MEMS gyroscope drift signal would overcome these shortcomings. After the original drift signal was filtered by the improved median filter, the wavelet decomposition on-line could be used to decompose the gyroscope drift signal into the coarse scale signal and the fine scale signal. The drift character would be extracted after reconstructing the coarse scale signal and the processed fine scale signal.

Ways of the time series analysis are often used in the modeling the drift signal. AR model can be used to model the random signal. After modeling the residual signal from the drift signal, the comparatively exact state space model and input-output model were built for the Kalman filter. Adaptive Kalman filter is an improved Kalman filtering. It makes good use of the measurement data to modify the time-varying parameters of the filter equation continually.

The DSP had been implemented by a TMS320F281X digital signal processor. Finally, we had a digital MEMS gyroscope. And the de-drift algorithms of the DSP was also fit for the gyroscope dynamic signal processing.

II. HOW TO GET RID OF BURST NOISE AND OUTLIER SIGNAL FROM DRIFT SIGNAL

In the measurement signal from the MEMS gyroscope, there often appeared some burst noise and outlier signal. It would affect the following character extracting of the drift signal. So drift signal was pre-processed to reduce the burst noise and outlier signal. A simple median filter, together with the mean filter, was designed to filter the original signal [1]. The median filter equation was as follows:

$$y_{m+1} = median(\frac{x_1 + x_2 + \cdots + x_m}{m} + x_{m+1} + \frac{x_{m+2} + x_{m+3} + \cdots + x_{2m+1}}{m}) \quad (1)$$

where the $median(*)$ was median function. In order to reduce burst noise and outlier signal, the data window width $2m+1$ would be selected carefully so that the useful signal would be kept. m was often selected from 3 to 5. Result of the improved median filter was shown in Fig. 1. All data was from the MEMS gyroscope measurement in an hour. The width of data window was $2m+1=7$. Seen from the figure, the burst noise and outlier signal was reduced effectively.

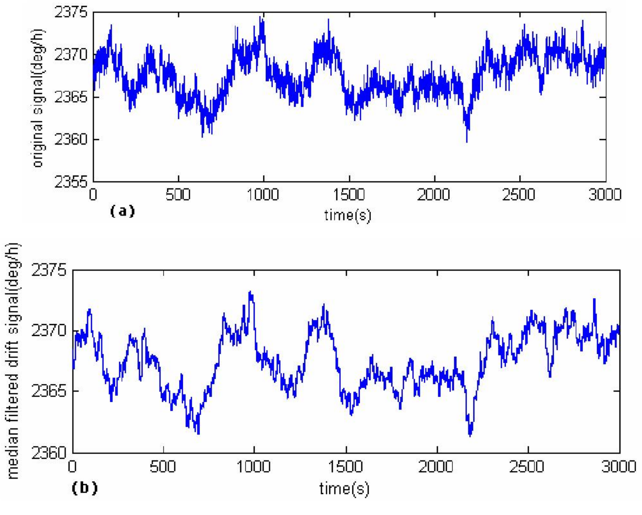

Figure 1. Comparison of Filtered and Un-filtered Drift Signal. (a) Drift Signal before Median filtering. (b) Drift Signal after Median Filtering

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III. DRIFT CHARACTER EXTRACTION BY WAVELET TRANSFORMATION

Because of the existing noise and large drift, it was difficult to use polynomial fitting to extract the trend item of the drift signal. Wavelet decomposition on-line was used to implement the processing.

The wavelet decomposition was used to decompose the drift signal into the coarse scale signal and the fine scale signal. The coarse scale signal was mainly made up of the low-frequency useful signal and the fine scale signal, where the fine scale signal was mainly made up of the high-frequency noise. Frequency of the drift signal was comparatively low. The drift character of the gyroscope could be described by the coarse scale signal [2][3][4]. When the signal was reconstructed, the fine scale signal was set to zero or the value of soft threshold and the coarse scale signal was reserved.

Usually, the multi-scale wavelet decomposition often had long delay and sidewall effect. It was also difficult to be implemented on-line. An on-line wavelet decomposition of the Haar wavelet basis had been selected to decrease the noise, the delay and the sidewall effect. The decomposition precision was also increased. By setting the width of the data window as 2^N, steps of the drift signal character extraction by the Haar wavelet basis was just as follows [1]:

Step1 Decompose the median filtered signal into coarse scale signals and the fine scale signals of L levels by the Haar wavelet basis decomposition. The L was often from 5~8.

Step2 Reconstruct the decomposed signal by setting the fitful soft threshold value to the fine scale signals from every level decomposition.

Step3 Shift the data window to let the newly sampled data come into. Continually change the width of the data window in order to let the width approach to the fixed 2^N. The N was decided on the computation burden and was often selected from 5 to 8.

Step4 Return to step2 and repeat the step 2 ,3.

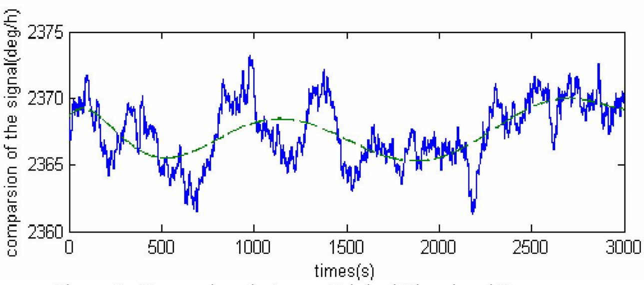

Figure 2. Comparison between Original Signal and Gyroscope Drift Character Curve

Result of the effectively extracted gyroscope drift character was shown in Fig. 2. The algorithm could be finished in real-time on line. In order to alleviate the processor processing burden and meet the need of the real-time implement, N was selected as 2^6.

IV. AR MODEL AND ADAPTIVE KALMAN FILTER

Define the residual signal (see Fig4) as the D-value between the original drift signal and the wavelet decomposed signal. In order to decrease affect of the noise on the practical measurement from the MEMS drift, the time series analysis was used to model the residual signal and set up the Kalman filter matrix equation. Before modeling the residual signal, stationarity and periodicity of the residual would be judged.

After the periodical signal among the residual signal was subtracted, the stationarity was judged by the series auto-correlation function. When the series of extracted periodicity was not stationary, the one order differential or two order differential of the series would make them stationary [5].

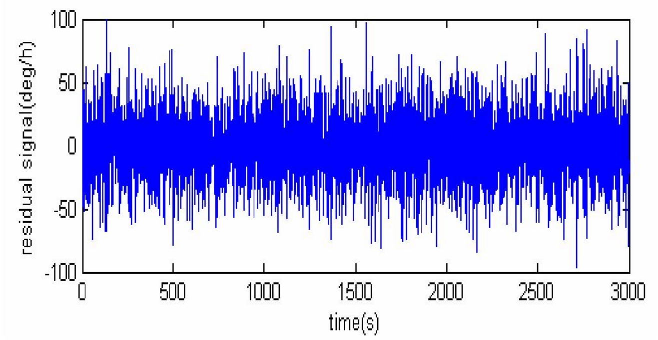

Figure 3. Residual Signal

Based on the character of the auto correlative function and the feasibility of the hardware implementation, a two-order AR model was built to model the residual signal. The two-order AR model equation was

$$x_n = -a_1 x_{n-1} - a_2 x_{n-2} + \varepsilon_n \quad (2)$$

Kalman filter is a linear recursive estimate of the signal. The filtering result is the optimal of lest mean variance. After the $AR(2)$ model of the residual signal is built, the Eq (2) can be changed into the status space model and the input-output model just as the follows [6]:

$$X_n = -a_1 X_{n-1} - a_2 X_{n-2} + \varepsilon_n = \Phi_n X + \Gamma_n \varepsilon_n \quad (3)$$

$$Y_n = X_n + v_n = H_n X_n + v_n \quad (4)$$

where ε_n is the observe noise, v_n is the measure noise, whose respective variance is Q_n and R_n. And Q_n also stands for the variance of the residual signal. Usually, R_n is one tenth of Q_n. Thus, Kalman filter matrix equations are as [7]

$$P_{k+1,k} = \Phi_k P_{k,k} \Phi_k^T + \Gamma_k Q_k \Gamma^T \quad (5)$$

$$G_{k+1} = P_{k+1,k} H_{k+1}^T [H_{k+1} P_{k+1,k} H_{k+1}^T + R_{k+1}]^{-1} \quad (6)$$

$$P_{k+1,k+1} = [I - G_{k+1} H_{k+1}] P_{k+1,k} \quad (7)$$

$$\hat{X}_{k+1,k} = \Phi_k \hat{X}_{k,k} \quad (8)$$

$$\hat{X}_{k+1,k+1} = \hat{X}_{k+1,k} + G_{k+1}[y_{k+1} - H_{k+1} \hat{X}_{k+1,k}] \quad (9)$$

where y_{k+1} is the unfiltered data.

Among the Kalman filter matrix equations, $\hat{X}_{k+1,k+1}$ is the output of the filter. $y_{k+1} - H_{k+1}\hat{X}_{k+1,k}$ is the D-value between the prediction and the practical measurement. G_{k+1} is a time-varying gain vector. It is the correcting degree to the prediction error. From the theory view, the Kalman filter algorithm will give the more accurate estimate for the parameters when number of the processed data increases. Error between the parameter estimation and the parameter real value will become lager and larger. In fact, with the times increase of the iteration, $P_{k+1,k+1}$ will be less and less and will approach to zero. The new data will be submerged by the old data. In order to prevent the data saturate and get the adaptive estimation of the time-varying measure system, the Kalman filter algorithm will be modified by decreasing the effect from the old data. Weighting the old data by using the fading factor can strengthen the new data effect. If the algorithm convergences, the measure noise and the observe noise will become less and less. Multiplying Q_n and R_n a fading factor will speed up the algorithm convergence. The adaptive Kalman filter equations are described as [8]

$$P_{k+1,k} = \Phi_k P_{k,k} \Phi_k^T + \Gamma_k \alpha Q_k \Gamma^T \qquad (10)$$

$$G_{k+1} = P_{k+1,k} H_{k+1}^T [H_{k+1} \alpha P_{k+1,k} H_{k+1}^T + \alpha R_{k+1}]^{-1} \qquad (11)$$

$$P_{k+1,k+1} = \frac{1}{\alpha}[I - G_{k+1} H_{k+1}] P_{k+1,k} \qquad (12)$$

$$\hat{X}_{k+1,k} = \Phi_k \hat{X}_{k,k} \qquad (13)$$

$$\hat{X}_{k+1,k+1} = \hat{X}_{k+1,k} + G_{k+1}[y_{k+1} - H_{k+1} \hat{X}_{k+1,k}] \qquad (14)$$

where α is a weighting fading factor and $0 < \alpha \leq 1$. Fuzzy control and the neural network can get the accurate α off-line. When data is filtered on-line, the α can be set as a fixed value, approaching to 1. After the residual signal is modeled by the two-orders AR model and is filtered by the preceding adaptive Kalman filter, accuracy of the measurement had been improved greatly. By using the

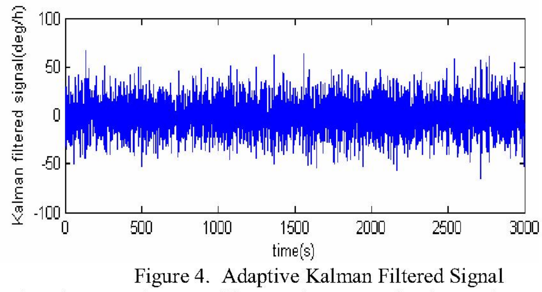

Figure 4. Adaptive Kalman Filtered Signal

adaptive Kalman filter, the standard variance of the residual signal of the static drift of the MEMS gyroscope was 36.32 deg/h. But by using the normal Kalman filter, the standard variance of the residual signal was be 45.51 deg/h. The α was set as 0.995 and all the data was from the practical measurement in an hour. Result of the adaptive Kalman filter from the static measurement of the MEMS gyroscope was shown in Fig. 4. Processing procedure of all the data was shown in the Fig. 5.

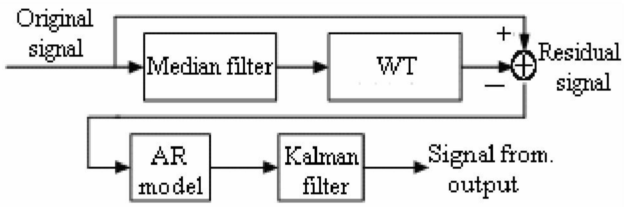

Figure 5. Procedure of DSP

In order to verify validity of the algorithm, the dynamics measurement of the MEMS gyroscope had been processed by the preceding ways, where the dynamics signal was made up of the original drift signal and different frequency and amplitude sine signal. Comparison between the dynamic measurement and the static measurement of the gyroscope was shown in Fig. 7 and Fig. 8.

At last, the DSP was implemented in a chip of the digital signal processor of the TMS320F281X. The standard variance of the dynamics de-drift signal could be decreased from the original 80.42 deg/h to 18.31deg/h.

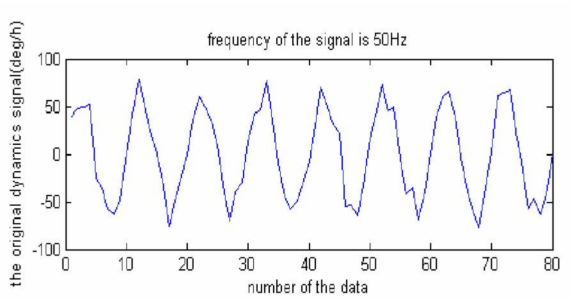

Figure 6. Original Dynamics Signal

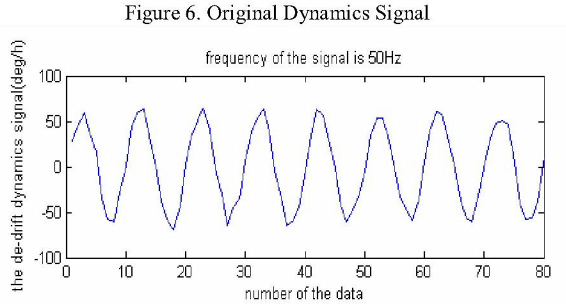

Figure 7.De-drift Dynamics Signal

V. CONCLUSION

The burst noise and outlier signal could be got rid of by the improved median filter. After extracting the drift character by the wavelet transformation and modeling the residual signal, the observing model and the state space model were built for the Kalman filter.

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