Comparison of Multisensor Fusion Techniques for Improvement of Measurement Accuracy with MEM Accelerometers

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Abstract: - In this study, an adaptive filter based multisensor fusion system is designed to reduce the effect of mechanical Brownian noise in the output value of multiple MEM accelerometers on a single die system. To this aim, a Kalman Filter (KF) based sensor fusion algorithm is developed and simulated. The results are evaluated with respect to the case with no fusion process as well as with Least Mean Squares (LMS) based sensor fusion algorithms, also simulated for comparison. The results demonstrate the superiority of KFs in comparison to other techniques for the sensor fusion of multiple MEM accelerometers on single die system.

Key-Words: - multisensors**,** MEM accelerometers, sensor fusion, Kalman Filters (KFs), Least Mean Square (LMS).

1 - Introduction

Microelectromechanical (MEM) systems have been in the market for nearly 20 years and in research laboratories for almost 40 years now, serving a variety of areas from aerospace and automotive to biomedical and military applications. Being mostly used as sensors so far, currently, the most popular MEM devices in the market are inertial sensors.

Most of the research in the past years has been on seeking ways to improve sensor performance. This was started by changing the semiconductor process and making new foundries, which is somewhat effective and yet an expensive approach. Changes were also made to the mechanical design [11] and to the existing topologies[12], as well as low noise low drift electronic read-out circuitry. [13]

In this study, adaptive filter based sensor fusion techniques are developed and tested to improve the performance of the sensors. In spite of numerous studies on adaptive filter based sensor fusion, the major contribution of this study is the integration of those sensor fusion techniques with MEM sensors, in an effort to improve the measurement accuracy of those significantly low cost devices. To the authors' best knowledge, there is no reported study on a similar approach to address the problem.

The main objective of the paper is the reduction of mechanical noise in MEM accelerometers to improve measurement accuracy. To achieve this aim, two sensor fusion algorithms which use well known adaptive filters, -namely, Least Mean Square (LMS) and Kalman Filters (KFs)- are developed and compared in terms of the resulting measurement accuracy. The methods are tested for the sensor fusion of 3 accelerometers; namely, two of identical nature (1-DOF) and one, 6-DOF accelerometer.

2 - Dynamic Model of MEM Accelerometers

Accelerometers are typically constructed in a mass-spring-damper structure as shown in Fig. 1. Generally in silicon processing, the mass is realized by thick silicon, and the spring is realized by thin silicon, while damping occurs based on fluid dynamic principles. When an acceleration effect is created on the mass, a force of F= m·a is applied to the spring, which is thus deflected until its elastic force equals the force produced by the acceleration. Neglecting the damping , it can be said that the force acting on the spring is proportional to its deflection, x with $F=k\cdot x$, so in case of no movement, the deflection is proportional to the acceleration[3],

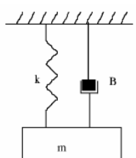

Figure 1: Mechanical Structure of an Accelerometer. [1]

although under normal conditions, a damping force $F_d = - B \cdot v$ has to be considered. The movement is then described by the equation of a forced and damped oscillator [2]:

$$m\frac{d^2x}{dt^2} + B\frac{dx}{dt} + kx = ma_{ext} \quad (1)$$

where m represents the proof mass of the sensor, B represents damping constant, k represents spring constant of the support and a_{ext} represents acceleration of global system. [2]

The following parameters can be defined [2]:

- Mechanical sensitivity: $S_m = \frac{m}{k}$

- Natural Frequency: $w_n = \sqrt{\frac{k}{m}}$

- Damping Factor: $z = \frac{B}{2\sqrt{km}}$

2- Noise Model of MEM Accelerometers

All noise sources, whether mechanical or electrical, affect the overall accelerometer resolution. There are four noise components in MEM accelerometers: Brownian, kT/C, amplifier and quantizier noise.[5]

The mechanical noise is due to the Brownian motion of the proof mass and is called Brownian noise. The mechanical noise might be reduced by proper accelerometer design and by reducing the damping factor and using a larger mass. However, this method has some disadvantages in terms of reliability [5].

A major noise source in switched-capacitor circuits is kT/C noise which is generated by the thermal noise sampling of the switches [5].

The readout circuitry uses correlated double sampling to cancel the input CMOS amplifier flicker noise. This noise is amplified by the ratio of total input capacitors (including the parasitic) to the integrating capacitor [5].

The effective quantization noise is related by the resolution of ADC. As the resolution is increased, quantization noise decreases. Thus, quantization noise can be reduced, if not totally eliminated[5].

As shown in the Figure 3.1 when acceleration takes place, a mechanical noise also occurs in the accelerometer, which is called Brownian noise. The kT/C noise occurs in the amplifier part of the circuit, as explained previously, in the sample and hold circuits and sC (switch Capacitor) filters. Finally, the quantization noise occurs in the quantization part of the circuit.

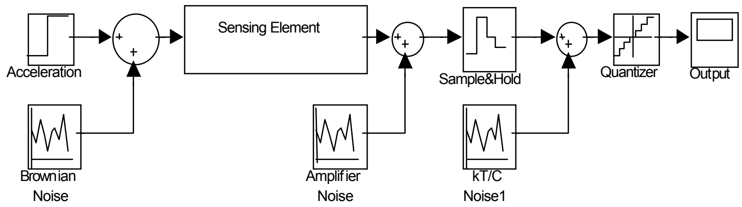

Figure 2: Noise model of MEMS accelerometer [5]

This study does not deal with quantization, kT/C or amplifier noises, as methods do exist in the literature to reduce their effects. However, the only existing methods against Brownian noise have an adverse effect on reliability; hence, the concentration of this study is on reducing the Brownian noise using sensor fusion techniques without compromising reliability.

3- Sensor Fusion using Kalman Filters

A general linear discrete-time system under the effect of Gaussian noise can be formulated with the following equations:

$$z_k = C_k x_k + v_k, v_k \sim N(0, R_k) \quad (2)$$

$$x_K = A_{k-1}x_{k-1} + B_{k-1}u_{k-1} + w_{k-1}, w_k \sim N(0, Q_k) \quad (3)$$

where z_k: measurement vector, x_k : state vector, A : state transition matrix, B: control matrix, C: measurement matrix, w_k : measurement noise vector, which is Brownian noise in this study; v_k : measurement noise vector, which is another noise source in this study.

As shown in the Equation 2, v_k is zero mean Gaussian noise whose covariance is R_k. Respectively from (3), w_k is zero mean Gaussian noise whose covariance is Q_k.

The Kalman filter(KF) uses the system model in (2) and (3) to propagate the estimated states:

$$\hat{x}_k = A_{k-1}\hat{x}_{k-1}(+) + B_{k-1}u_{k-1} \quad (4)$$

The plus sign on $x_{k-1}(+)$ indicates that the estimate has been updated with a measurement at time k-1. The state estimate update in (4) does not equal the true state update in (3) as the estimate in general differs from the true state, also because the contribution from the process noise, W_k, is unknown. Therefore the covariance of the estimation, P, needs also to be calculated: [10]

$$P_k = A_{k-1} P_{k-1}(+) A_{k-1}^T + Q_{k-1} \quad (5)$$

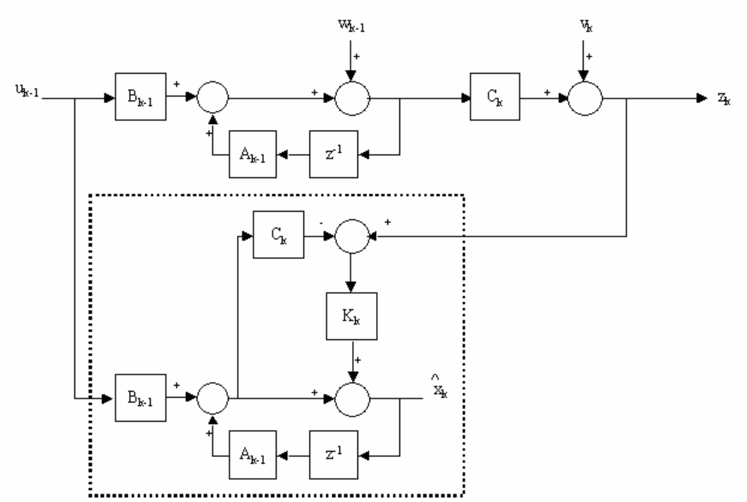

Figure 3: Linear discrete system with Kalman filter [10]

If a measurement is available, the estimate is updated by fusing the incoming data with a gain, K_k, which is calculated using the following equations:

$$K_k = P_k C_k^T \left[C_k P_k C_k^T + R_k \right]^{-1} \quad (6)$$

$$\hat{x}_k(+) = \hat{x}_k + K_k \left[z_k - C_k \hat{x}_k \right] \quad (7)$$

The gain, K_k, is called the Kalman gain and is the gain that minimizes the covariance matrix, P(+). The covariance after the fusion is:

$$P_k(+) = \left[I - K_k C_k \right] P_k \quad (8)$$

$$\in_k = z_k - \hat{z}_k \quad (9)$$

$\in$ is called the innovation and is the difference between predicted and actual measurements. When the filter operation reaches steady state, the innovation should be a zero-mean white noise sequence. This property provides a useful means to monitor the optimality of the filter and detect various inconsistencies [10]; i.e if the innovation can not attain a zero-mean white noise sequence, it can be interpreted that there is a problem with the mechanical part of sensor, or with the dynamic parameters of the sensor.

The fact that most systems can never be perfectly modeled and that noise distributions hardly ever are known accurately often sets the limits for the achieved performance. However, even when the actual conditions are far from those assumed, the Kalman filter can often be stabilized and fine tuned by adjusting the process noise covariance matrix, Q. [10]

In this study, the KFs are run for each system separately and then the state estimates are fused to get a better state estimate by using the following relationship [7]:

$$\hat{x}_g = \frac{\sum \frac{\hat{x}_i}{P_i}}{\sum \frac{1}{P_i}} \quad (10)$$

As seen in (10), the smaller the error covariance of an estimate, the larger is its weight in the calculation of the global estimate.

4 LMS Based Sensor Fusion

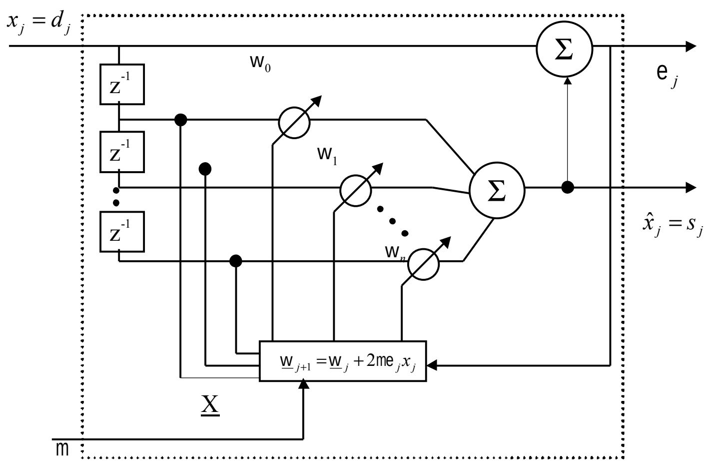

Figure 4: LMS Adaptive Filter [9]

Consider now the case where the input vector x is received by a tapped delay line as in Figure 4. Hence the input vector can be written as: [9]

$$\underline{x}_j^T = \left[1, x_j, x_{j-1}, .., x_{j-n+1} \right] \quad (11)$$

and the output of the sum, the estimated signal s_j can be written as:

$$\hat{x}_j = s_j = \underline{W}^T \underline{x}_j = w_0 + \sum_{i=1}^{n} w_i x_{j-i+1} \quad (12)$$

which is the autoregressive (AR) estimation. The LMS filter is an AR filter whose coefficients are adapted to

make the filter output and the desired input to have minimum mean square error. [9]
Setting $d_j = x_j$, $w_0 = w_1 = 0$, $w_i = -w_{i+1}$, i = 1, 2, ,,,, n leads to (12).

$$\hat{x}_j = \sum_{i=1}^{n-1} \bar{w}_i x_{j-i} \tag{13}$$

LPC (AR coefficients) of a nonstationary signal can be evaluated by using the following formula [9], in which μ represents a coefficient defining convergence speed.

$$\underline{W}_{j+1} = \underline{W}_j - 2\mu e_j \underline{x}_j \tag{14}$$

To use LMS filter in sensor fusion application, the LMS filters should be run in all the systems concurrently. Then the fused result is generated automatically. The LMS based sensor fusion approach used in this study is given below [9], for the fusion of two identical 1-DOF and one 6-DOF accelerometer:

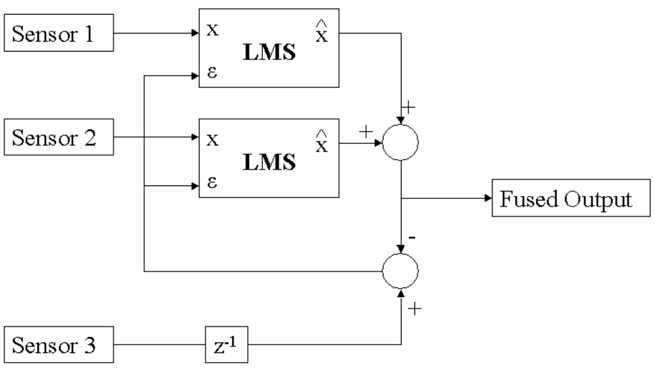

Figure 5: LMS Based Sensor Fusion Diagram

4 Simulation Results

In this section, the two sensor fusion algorithms will be tested with simulations for MEM accelerometers with known parameters. One set of these accelerometers shown in Figure 6 comprises of two standard 1 degree-of-freedom (DOF) double cantilever beam piezoresistive accelerometers, which is used to measure the z axis acceleration, while the third one is a 6-DOF accelerometer, of which only the z-axis information is used. For a realistic evaluation of the techniques, the possible mismatches between the two 'identical' 1-DOF accelerometers are also reflected to the simulation models, by giving 10% variation to the parameter values.

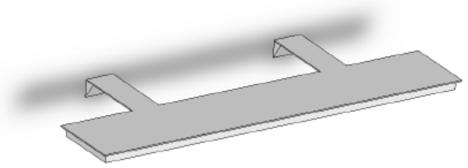

Figure 6: Double Cantilever Beam Piezoresistive Accelerometer [4]

The other accelerometer considered in the algorithm is 6-DOF piezoresistive accelerometer as demonstrated in Figure 7. In order to fuse its data with the other accelerometers in the algorithm, only the z axes acceleration data is used although it can give acceleration data in 6 axes,. Only one such accelerometer is considered in this algorithm [8].

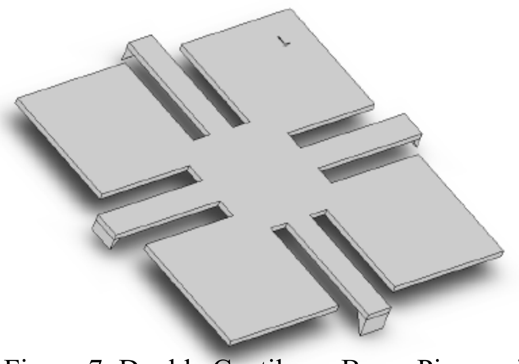

Figure 7: Double Cantilever Beam Piezoresistive Accelerometer [8]

The system dynamics is calculated separately for the two accelerometers; however, the general dynamics equations for all 3 accelerometers are the same, as only the z-axis is taken into account and the x axis and y axis of the third accelerometer is not taken into consideration. Using (1),

$$\frac{x}{a_{ext}} = \frac{1}{s^2 + (b/m)s + (k/m)} \tag{15}$$

where k, m and b values are critical; k is calculated as,

$$k = \frac{EWt^3}{L^3} \tag{16}$$

where E represents Young Module, L represents length of the beam, W represents width of the beam and t represents thickness of the beam[1].

Similarly, b is calculated as,

$$b = \frac{\eta A}{h_{top}} + \frac{\eta A}{h_{bottom}} \tag{17}$$

where η represents viscosity of gas surrounding the device (18uPa-sn for air), A is the area of plates and h is the distance between plates [6]. System parameters which are calculated from these equations are represented in Table 1.

	M (kg)	B (kg/sn^2)	K (kg/sn)
1st Accelerometer	1.8460e-11	4,9070e-7	22.6648
2nd Accelerometer	1.9485e-11	5,5818e-7	18,5440
3rd Accelerometer	7.6228e-11	3.3234e-6	3.4699

Table 1: Calculated System parameters

The performances of the techniques are compared in terms of RMS of errors, defined as below:

$$N = t / T \tag{18}$$

$$RMS(e[t]) = \frac{1}{N}\sqrt{\sum_{n=0}^{N}(a_c[nT] - a_{noiseless}[nT])^2} \tag{19}$$

where t : simulation time, T : sample period, N : total sampled data at time t, $a_{noiseless}$: applied acceleration in time nT in the simulation, and a_c: calculated acceleration in time nT. It could be the output of the inverse filter, Kalman Filter, LMS based SF filter or Kalman based SF filter depending on the simulated case.

The simulations are performed by adding noise sources to the system as shown previously in Figure 2. Noiseless and noisy acceleration outputs are calculated by processing the output from the inverse of system dynamics of the sensor, hereafter called, inverse filter.

Initially, to demonstrate the smoothing effect of the KF, each accelerometer is processed through an inverse filter as well as a KF and the outputs are compared. Figure 8 (a), (b), and (c) demonstrates the improvement made by using KFs for the outputs of each accelerometer type. Next, simulations are performed by applying the sensor fusion of the outputs using KF ,via (10). Figure 9 depicts the significant improvement made by the KF based sensor fusion technique over the other approaches in terms of noise elimination.

Next, simulations are also performed using LMS based fusion of the outputs to compare with KF based sensor fusion.. As can be seen from Figure 10(b), the actual acceleration data in Figure 10(a) is distorted due to the Brownian noise. The problem of noise causes reduced accuracy. To avoid this problem adaptive filters are used as explained previously; the result with KF based sensor fusion is given in Fig. 10 (c), while that obtained with LMS is in Fig. 10 (d) . It can easily be noted that both methods reduce the noise, which indicates that by sensor fusion, an improved measurement accuracy can be obtained.

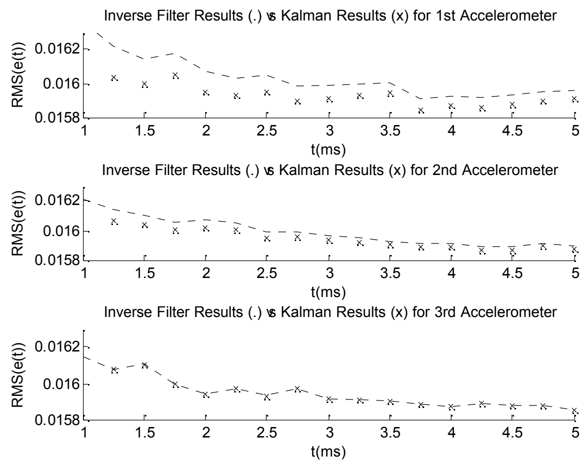

Figure 8: (a) Inverse Filter vs Kalman Filter for 1st 1-DOF Accelerometer, (b) Inverse Filter vs Kalman Filter for 2nd 1-DOF Accelerometer, (c) Inverse Filter vs Kalman Filter for 6-DOF Accelerometer

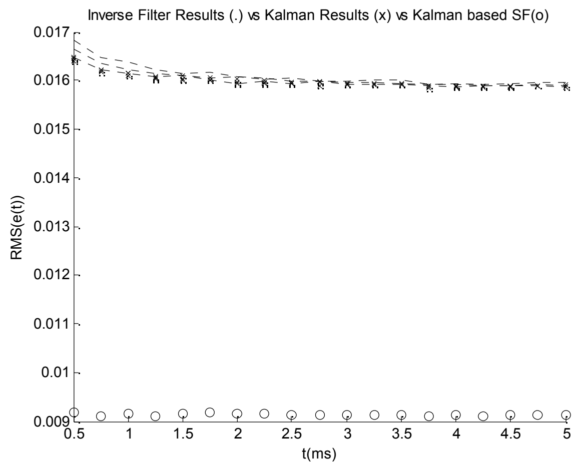

Figure 9: Measurement error using Inverse Filters vs individual KFs vs KF based Sensor Fusion

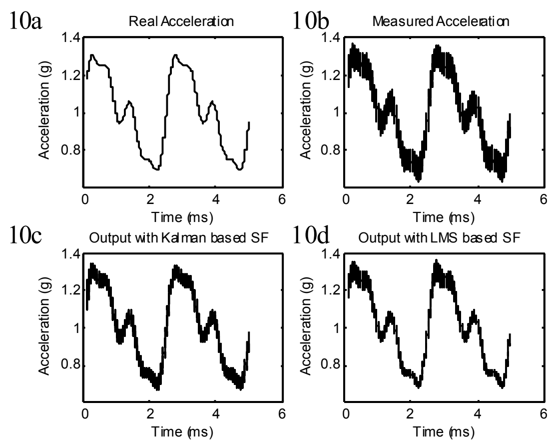

Figure 10: (a) Noiseless acceleration output, (b) Noisy acceleration output, (c) output which is fused with Kalman based Sensor Fusion, (d) output which is fused with LMS based Sensor Fusion.

Finally, the inverse filter, KF based sensor fusion and LMS based sensor fusion performances are compared in terms of the RMS values of the errors as presented in Figure 11. It can easily be observed that the noise levels of the adaptive filter based sensor fusion techniques are significantly lower than those of the inverse filter.

When Kalman and LMS based sensor fusion filters are compared, it can be demonstrated that the KF approach yields a superior performance, particularly in terms of its fast convergence rate, which is a well-known property of KFs and is noted to be considerably better than the LMS filter.

4 Conclusions

As a conclusion it can be summarized that although there are other techniques like process improvement, topology improvement, etc. for the performance improvement of MEM sensors, the accuracy of MEM sensors can also be improved by using adaptive filter based multisensor fusion techniques. In this study, this improvement is demonstrated with MEM inertial sensors. The proposed approach has some advantages over the conventional techniques because it is low cost and more flexible, and hence is motivating for use in conjunction with other MEM inertial devices like gyrometers, magnetometers etc.

In this study, KF and LMS based fusion techniques are also compared for MEM accelerometers. Both techniques are tested for the fusion of two 1-DOF and one 6-DOF MEM accelerometers and it has been concluded that a higher accuracy and faster convergence rate can be achieved by using KF based sensor fusion.

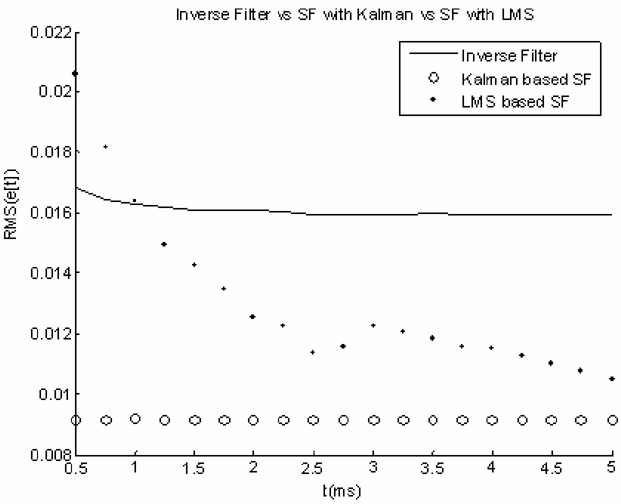

Figure 11: Comparison of errors obtained in inverse filter, SF with Kalman and SF and LMS

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