

**ATTITUDE DETERMINATION USING AN ADAPTIVE  
MULTIPLE MODEL FILTERING SCHEME**

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**1.0 Background & Problem Identification**

Attitude determination has been considered as a permanent topic of active research and perhaps remaining as a forever-lasting interest for spacecraft system designers. Its role is to provide a reference for controls such as pointing the directional antennas or solar panels, stabilizing the spacecraft or maneuvering the spacecraft to a new orbit. Least Square Estimation (LSE) technique was utilized to provide attitude determination for the Nimbus 6 and G. Despite its poor performance (estimation accuracy consideration), LSE was considered as an effective and practical approach to meet the urgent need and requirement back in the 70's. One reason for this poor performance associated with the LSE scheme is the lack of dynamic filtering or "compensation". In other words, the scheme is based totally on the measurements and no attempts were made to model the dynamic equations of motion of the spacecraft.

Another drawback of the LSE approach is the derivation of the variance matrix R (measurement noise covariance matrix). The LSE scheme employed by Nimbus 6 and G to compute the attitude determination literally "fix" the variance values of the roll and pitch components (per operating condition). For yaw and Digital Sun Aspect Sensor (DSAS) system components, even though they are "recursively" computed and updated on-line. They are derived from a "brute-force" approach rather than based on the "live" information or behaviors of the sensor reading (both DSAS and yaw attitude calculation from the Rate Measurement Package, RMP) to extract and update the measurement noise variances.

Other modern techniques applied to the attitude determination problem are the Kalman filtering or Extended Kalman filtering (EKF), H-infinity nonlinear estimation, or mixed  $H_2/H$ -infinity estimation. The Kalman filtering scheme is suitable for on-board attitude determination and for applications where constant tracking of a changing attitude is required. The technique is useful for on-board processing because it does not need to recycle through previously observed data and is frequently able to estimate the current state in real time. The Kalman filtering techniques (or  $H_2$ ) is carried out with the assumption that the noise characteristics (process noise and measurement noise covariance matrices) are known (in the sense that the noise is either random with known statistical properties or has a fixed and known spectrum). In reality, the noise characteristics or statistics are unknown. Furthermore, there are additional error sources such as modeling error, truncation error (round-off), or linearization error which tend to degrade the performance of traditional Kalman filters. Truncation or round-off errors may be partially solved by using a Kalman filter variation, called a square-root filter, which substitutes the square root of the error covariance matrix for its full value in the filter gain equation. Another useful variation which is as numerically stable as the square root filter but which requires less computation is the UDU<sup>T</sup> filter discussed by Bierman. To handle the noise variation uncertainties effects, adaptive filtering techniques have also been discussed and investigated to improve the performance accuracy of the Kalman filter.

**2.0 Proposed Approach**

We propose an adaptive filtering approach which employs a bank of Kalman filters to perform robust attitude estimation. The proposed approach, whose architecture is depicted in Figure 1, is essentially based on the latest proof on the interactive multiple model design framework to handle the unknown of the system noise characteristics or statistics. The concept fundamentally employs a bank of Kalman filter or submodel, instead of using fixed values for the system noise statistics for each submodel (per operating condition) as the traditional multiple model approach does, we use an on-line dynamic system noise identifier to "identify" the system noise level (statistics) and update the filter noise statistics using "live" information from the sensor model. The advanced noise identifier, whose architecture is depicted in Figure 2, is implemented using an advanced system identifier. To insure the robust performance for the proposed advanced system identifier, it is also further reinforced by a learning system which is implemented (in the outer loop) using neural networks to identify other unknown quantities such as spacecraft dynamics parameters, gyro biases, dynamic disturbances, or environment variations.

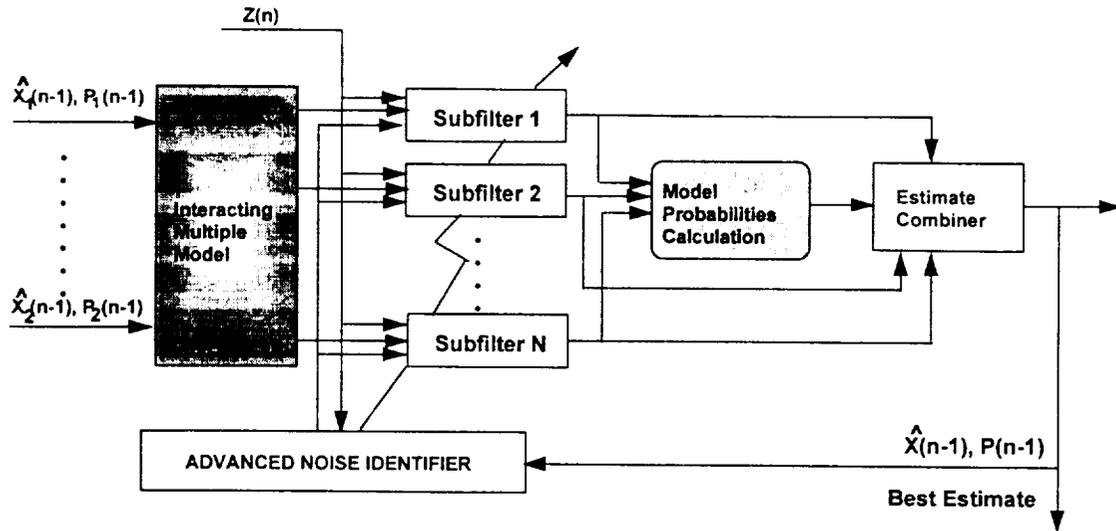


Figure 1: Attitude Determination Using Adaptive Multiple Model Filtering

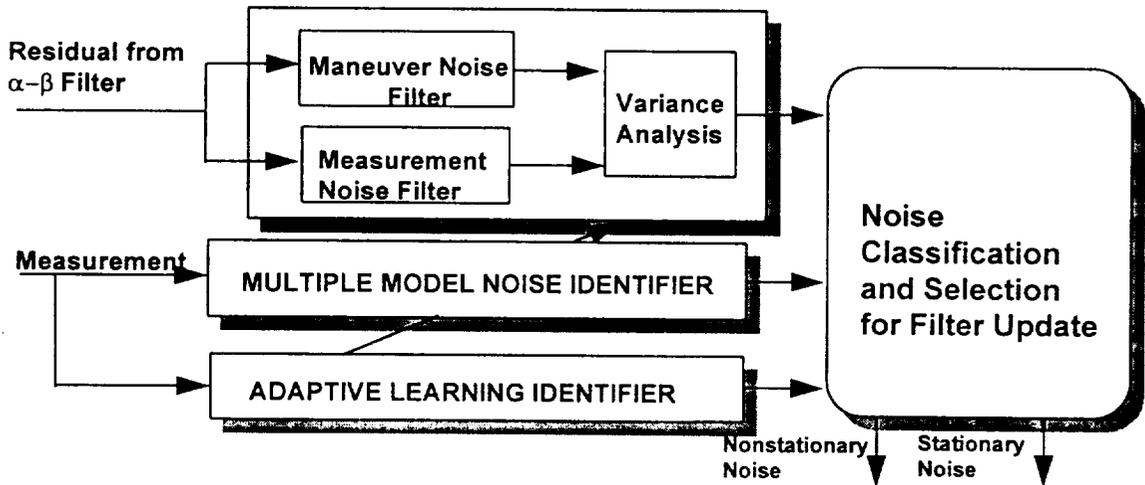


Figure 2: Architecture of Advanced Noise Identifier

The proposed noise identifier architecture will be implemented in such a way that it can handle all “noise spectrum” (e.g., stationary/nonstationary to white or color, etc.). The first two subsystems: a-b estimation scheme and interactive multiple model estimation scheme are strictly designed to handle noise identification while the third subsystem: Adaptive Learning Estimator is performing both noise and unknown parameter identification. The existence of the third subsystem is primarily intended for the performance improvement of the overall advanced system identifier.

**References:**

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