USING INERTIAL MEASUREMENT TO SENSE CRASH-TEST DUMMY KINEMATICS

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Abstract

In this study, the authors present a novel fuzzy-logic signal-processing and sensor-fusion algorithm with quaternion implementation to compute dummy kinematic parameters in a vehicle crash event using inertial sensing. This algorithm is called Quaternion Fuzzy Logic Adaptive Signal Processing for Biomechanics (QFLASP-B). This algorithm is efficient and uses 3 rates obtained using gyroscopes and 3 accelerations obtained using accelerometers (one gyro and accelerometer pair per axis) to compute kinematic parameters in a crash event. In this study, this QFLASP-B algorithm was validated using MSC-ADAMS and Life-Mod simulation software. In virtual simulations of crash testing, the problem of forward kinematics was solved using MSC-ADAMS and Life-Mod to obtain body accelerations and body angular velocities. The inverse kinematic problem of computing inertial solution using body rates and accelerations was solved using QFLASP-B.

The results of these two analyses were then compared. The results revealed close similarities. In the experimental validation, the solution obtained from the Nine Accelerometer Package (NAP) was compared with the solution obtained from the three gyros and three accelerometers, or Inertial Measurement Unit (IMU), using the QFLASP-B algorithm for head orientation computation. These results were also closely aligned. The QFLASP-B algorithm is computationally efficient and versatile. It is capable of very high data rates enabling real-time solution computation and kinematic parameters determination. The adaptive filtering in QFLASP-B enables engineers to use low-cost MEMS gyroscopes and accelerometers, about $30 each, which are typically noisy and show significant temperature dependence and bias drift—both short-term and long-term—to obtain meaningful and accurate results with the superior signal-processing and sensor-fusion algorithm. It is anticipated that this inertial tracking/sensing approach will provide an inexpensive alternative for engineers interested in measuring kinematic parameters in a crash event.

Introduction

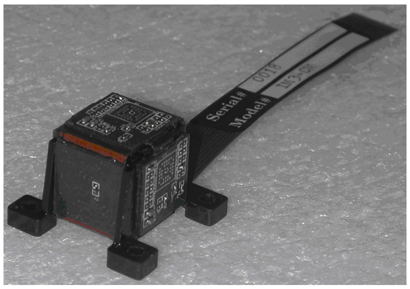
Motor vehicle accidents result in more than 40,000 fatalities and three million injuries each year in the United States. To increase occupant safety, it is important to study vehicle occupant kinematics and the mechanisms that generate the forces that injure vehicle occupants during crashes. Researchers have studied this problem from theoretical and practical aspects [1], [2]. Crash testing is routinely carried out to evaluate crashworthiness. Crash testing of dummies (Hybrid-II or III) and their kinematics plays a significant role in understanding occupant/pedestrian motion in crashes. There are various techniques currently used to record and understand vehicle–occupant or vehicle-pedestrian interaction. It is critical to know the positions and orientations of various body segments of a crash-test dummy in a typical crash event. This data is utilized to understand injury mechanism, severity of injury, effectiveness of seatbelts or airbags in order to determine the overall safety rating of the vehicle. There are various sensing techniques used to track the motion of a dummy in the crash scenario. Some of the widely used techniques for motion capture and sensing are high-speed video, accelerometry Nine Accelerometer Package (NAP) and inertial sensors [1]-[4]. Similar techniques are also used in Augmented Reality (AR) and Virtual Reality (VR) applications [5]-[6] for motion sensing.

The objective of this study was to present a novel software signal-processing algorithm and its applications to compute dummy kinematic parameters using inertial sensing. Currently, the sensors used for crash testing (like ATA rate-sensors gyroscopes and Endevco accelerometers) are very expensive, bulky and have strict power-conditioning and mounting requirements. In other words, using a sensor suit made up of currently-available hardware is not only expensive but also time consuming. Fortunately, recent advances in Micro Electro-Mechanical Systems (MEMS) technology have brought solid-state, integrated low-cost MEMS accelerometers and gyroscopes to market, which can theoretically be used for sensing applications.

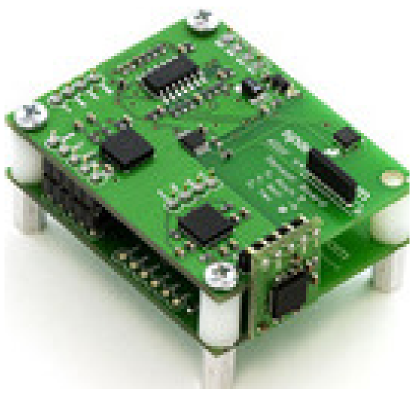
These MEMS sensors, despite their low cost, suffer from drift, scale-factor nonlinearity, noise and cross-axis errors [7]. It is almost impossible to use these sensors directly for crash testing applications. In this study, the authors present a smart Fuzzy Logic Adaptive Signal Processing (FLASP) algorithm that would enable engineers to use these low-cost MEMs sensors for accurate inertial sensing of kinematic parameters.

Some of the commercially-available IMUs are shown in Figure 1 [8]-[10]. In this study, Archangel's IMU, known as

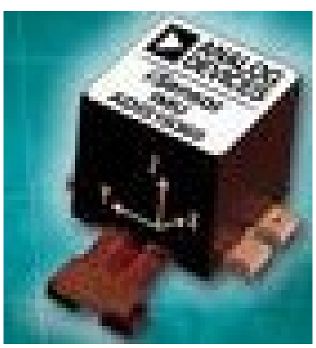
IM3 (Inertial Measurement Cube), was used to implement the QFLASP-B algorithm. IM3 is a six-axis Inertial Measurement Unit (IMU) system in a single ¾” cube. This cube measures and thermally compensates accelerations in 3 orthogonal axes (local X, Y and Z) and rotational velocities in three orthogonal axes (about local X, Y and X) and computes orientations, positions and velocities via an onboard DSP.



a) Archangel IM3



b) Sparkfun IMU



c) Analog Devices IMU

Figure 1. Inertial Measurement Units

The algorithm for inertial sensing (QFLASP-B) presented here runs on a low-cost DSP such as a DsPIC used by IM3, uses noisy measurements from MEMs sensors and produces equally accurate solutions obtained by high-cost precision sensors. This algorithm implements sensor-error models that minimize systemic errors. Typically, for IMUs, signal-processing algorithms based on Kalman filtering are used [11]-[13] for sensor fusion. Unfortunately, sensor-fusion algorithms using Kalman filtering involve numerous matrix inversions and cannot be implemented on a low-cost DSP platform when high-update rates (100 Hz or more) are needed. The QFLASP-B algorithm proposed here does not involve any matrix inversions and can be implemented on a low-cost DSP with computing solutions at frequencies of 100Hz or more. This algorithm is presented in section 2, followed by its embedded implementation, simulation, and testing results in section 3. Finally, section 4 summarizes the work.

An Algorithm for Inertial Sensing

The motivation for QFLASP can be explained by considering attitude-estimation problems with strap-down sensors, usually cast as a two-vector Wahba problem [15]. Given measurements of two non-co-linear vectors in a fixed-body frame, and with knowledge of the vectors in a reference frame, Wahba proposed an estimate of attitude by reducing the error between the reference vector set and the rotated vector set from the fixed-body frame. The use of quaternion representation eliminates the singularity issues associated with Euler-angle representations [16], [17]. The algorithm uses measurements from a fixed-body triad of gyros and accelerometers.

The estimation problem requires two frames – a fixed-body frame and a non-rotating inertial-reference frame. Let a and b represent the reference frame and the fixed-body frame, respectively. The attitude can be represented by a sequence of three right-handed rotations from the reference frame to the body frame. If ψ, θ and ϕ represent the rotations about the z axis and the intermediate y and x axes, respectively, a vector u^a in the reference frame can be transformed to a vector u^b with the rotation matrix $C_{b/a}$.

$$\mathbf{u}^b = \mathbf{C}_{a/b}\, \mathbf{u}^a \qquad (1)$$

The rotation matrix is given by

$$\mathbf{C}_{a/b} = \begin{bmatrix} c\theta c\psi & c\theta s\psi & -s\theta \\ -c\phi s\psi + s\phi s\theta c\psi & c\phi c\psi + s\phi s\theta s\psi & s\phi c\theta \\ s\phi s\psi + c\phi s\theta c\psi & -s\phi c\psi + c\phi s\theta s\psi & c\phi c\theta \end{bmatrix} \qquad (2)$$

where c and s = cos and sin , respectively.

For a 3-2-1 rotation sequence, Euler-angle representation has a singularity at $\theta = \frac{\pi}{2}$, where the roll and yaw angles are undefined. An alternate representation of attitude is with a quaternion. Quaternions are generalizations of complex numbers in three dimensions, and are represented by

$$\mathbf{q} = [q_0 \quad q_r]^T \tag{3}$$

where q_0 and q_r are the real part and the vector part of the quaternion. If the norm of the quaternion is unity, it is referred to as a unit quaternion. Just like the rotation matrix, a unit quaternion (or any quaternion in general) can be used to rotate a vector from a reference frame to a fixed-body frame. The rotation equation in terms of quaternion is expressed as

$$\mathbf{u}^b = \mathbf{q}^{-1} \cdot \mathbf{u}^a \cdot \mathbf{q}$$
$$\mathbf{q}^{-1} = \begin{bmatrix} q_0 \\ -q_r \end{bmatrix} \tag{4}$$

where $\mathbf{q}^{-1}$ is the inverse of the unit quaternion $\mathbf{q}$ and $\mathbf{q}$ is the unit quaternion that rotates a vector from system a to system b [17]. The attitude quaternion can also be represented as a product of component quaternions in three axes.

$$\mathbf{q}_\phi = [\cos(\phi/2) \quad \sin(\phi/2) \quad 0 \quad 0]^T \tag{5}$$

$$\mathbf{q}_\theta = [\cos(\theta/2) \quad 0 \quad \sin(\theta/2) \quad 0]^T \tag{6}$$

$$\mathbf{q}_\psi = [\cos(\psi/2) \quad 0 \quad 0 \quad \sin(\psi/2)]^T \tag{7}$$

The quaternion $\mathbf{q}$ can be derived from the component quaternions as

$$\mathbf{q} = \mathbf{q}_\psi \cdot \mathbf{q}_\theta \cdot \mathbf{q}_\phi \tag{8}$$

Poisson's kinematic equation in quaternion form that relates the rate of change of the attitude quaternion to the angular rate of the body frame with respect to inertial frame [17] is given by

$$\dot{\mathbf{q}}_{b/a} = 0.5 \cdot \mathbf{q}_{b/a} \cdot \boldsymbol{\omega}_{b/a} \tag{9}$$

If $\mathbf{q}_1$ and $\mathbf{q}_2$ are two quaternions, the relative orientation or the error quaternion between the two is

$$\mathbf{q}_e = \mathbf{q}_1 \cdot \mathbf{q}_2^{-1} \tag{10}$$

The two frames, whose attitude quaternions with respect to a reference frame, are $\mathbf{q}_1$ and $\mathbf{q}_2$ and coincide only if

$$\delta\mathbf{q}_e = 1 \text{ and}$$
$$\delta\mathbf{q}_e^r = 0 \tag{11}$$

where $\delta\mathbf{q}_e$ and $\delta\mathbf{q}_e^r$ are the real and vector parts of the quaternion error. $\delta\mathbf{q}_e^r = 0$ is a sufficient condition for the two frames to coincide.

Algorithm Description

The algorithm presented here uses measurements from three axis gyros and accelerometers. If ω_T is the true angular rate and ω is the measured angular rate, then

$$\omega = \omega_T + \varepsilon_B + \varepsilon + \eta \tag{12}$$

where ε_B is a time-varying bias, η is noise, and ε is other errors. If gyro bias can be captured with an active bias estimation scheme, then the estimate of the true angular rate is given by

$$\bar{\omega} = \omega - \bar{\varepsilon}_B - \varepsilon_\omega \tag{13}$$

where $\bar{\varepsilon}_B$ is the current estimate of the gyro bias and ε_ω is an angular rate correction derived from the attitude error. The estimate of angular rate is used to compute an attitude estimate from the gyros by the integration of equation (9). Expressed in matrix form, equation (9) is given by

$$\begin{bmatrix} \dot{q}_0 \\ \dot{q}_1 \\ \dot{q}_2 \\ \dot{q}_3 \end{bmatrix} = \begin{bmatrix} 0 & -\omega_x & -\omega_y & -\omega_z \\ \omega_x & 0 & \omega_z & \omega_y \\ \omega_y & -\omega_z & 0 & \omega_x \\ \omega_z & \omega_y & -\omega_x & 0 \end{bmatrix} \begin{bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \end{bmatrix} \tag{14}$$

where $\omega_x, \omega_y, \omega_z$ are estimates of the true angular rates in the x, y and z axes. Given an initial attitude estimate, equation (14) can be integrated to obtain the latest attitude estimate, $\mathbf{q}_0$. A reference attitude estimate is obtained from accelerometers. The accelerometer measurements are given by

$$\dot{\mathbf{v}}_I = \dot{\mathbf{v}}_B + \boldsymbol{\omega} \times \mathbf{v}_B + \mathbf{G} \tag{15}$$

where $\mathbf{v}_B, \mathbf{v}_I$ are body and inertial velocities, respectively, $\mathbf{G}$ is the gravity vector component in the body coordinates given by

$$\mathbf{G} = [g\sin\theta \quad -g\cos\theta\sin\phi \quad -g\cos\theta\cos\phi]^T \tag{16}$$

If a measure of forward velocity in the body frame is not available, the roll and pitch angles obtained from accelerometers are corrupted by the linear acceleration and the cross product terms involving angular rate and linear velocity. If the reference attitude quaternion is $\mathbf{q}_I$, the attitude error using equation (11) is given as

$$\mathbf{q}_e = \mathbf{q}_I \cdot \mathbf{q}_0^{-1} \tag{17}$$

If the attitude error is small, $\mathbf{q}_{e0} \approx 1$ and $\mathbf{v} = [q_{e1} \quad q_{e2} \quad q_{e3}]$ can be assumed to be the errors in roll, pitch and yaw attitudes. The quaternion error can be used to generate angular rate corrections using

$$\boldsymbol{\varepsilon}_\omega = \mathbf{k} \cdot \mathbf{v} \tag{18}$$

where $\mathbf{k}$ is an estimator gain. The angular rate correction is used as a feedback correction as given in equation (13).

The main features of QFLASP are

1. Adaptive Switching/Filtering: The data flow is altered at runtime. Thus, certain filters are activated or deactivated based on quality, consistency, and characteristics of data. The switching is implemented by means of Fuzzy Logic (discussed in next section). The Fuzzy estimator consists of a fuzzification process, an inference mechanism, a Rule Base and a defuzzification process. The fuzzification process assigns a degree of membership to the inputs over the Universe of Discourse. As the error changes, the degree of certainty changes and other measures of μ have non-zero values. Thus, the errors are encoded by the degree of certainty that are between certain error bounds. The values for the error bounds (E_1, E_2) can be determined using center clustering techniques on actual crash-test experimental data. Likewise, input membership functions are determined for the change in error. This process is explained in detail in the next section.

2. Adaptive Gain Tuning: The gains of the body-rate error, inertial-rate error and delay are tuned during runtime. Thus, the algorithm tunes itself to provide an optimum solution. In fact, the QFLASP-B output accuracy improves with period of use. The residual drift in the gyros and accelerometers is removed by means of feed-forward filters and are implemented in an error-correction loop.

3. Gravity Compensation: Accelerometers measure specific force, i.e., the accelerometer does not measure gravity but rather the component of total acceleration minus gravity along its input axis. The gravity-compensation function in QFLASP acquires data from accelerometers, based on the characteristics and validity of data, using appropriate filtering and passes slaving information to a sensor-fusion algorithm.

The governing equation for IMU dynamics are given as

$$\begin{aligned} \dot{\theta} &= \omega_y \cos\phi - \omega_z \sin\phi \\ \dot{\phi} &= \omega_x + \omega_y \sin\phi \tan\theta + \omega_z \cos\phi \tan\theta \\ \dot{\psi} &= (\omega_y \sin\phi + \omega_z \cos\phi)\sec\theta \end{aligned} \qquad (19)$$

The acceleration equations are given as

$$\begin{aligned} ax_{cg} &= \dot{U} + \omega_y W - \omega_z V + g\sin\theta && (a) \\ ay_{cg} &= \dot{V} + \omega_z U - \omega_x W - g\cos\theta\sin\phi && (b) \\ az_{cg} &= \dot{W} + \omega_x V - \omega_y U - g\cos\theta\cos\phi && (c) \end{aligned} \qquad (20)$$

where ω_x, ω_y and ω_z are body-angular velocities about x, y, z directions, respectively, and θ, ϕ and ψ are pitch, roll and yaw (inertial) angles. U, V, W are body velocities in the x, y, z directions, respectively, and ax_{cg}, ay_{cg} and az_{cg} are inertial accelerations. It should be noted that equation (19) is a coupled equation in angular velocities but does not involve any acceleration term. Equation (20) involves accelerations as well as body rates. Thus, discrete version of equation (19) is solved in an outer loop and equation (20) is solved in the inner loop to determine kinematic parameters—e.g., roll, pitch, yaw, inertial velocities, and positions—via integration.

Quaternion Fuzzy Logic

QFLASP is a novel approach for removing sensor errors. FLASP, like Fuzzy Logic from which it is derived, is a more intuitive process than Kalman Filtering [16], [17]. As an example, the quaternion errors and gyro biases are calculated by this algorithm and used in an adaptive loop to remove their effects. The Fuzzy estimator consists of a fuzzification process, an inference mechanism, a Rule Base and a defuzzification process. The fuzzification process assigns a degree of membership to the inputs over the Universe of Discourse. Referring to Figure 2, if the error (e) in Euler angle k is zero, the degree of certainty, μ_0 (center membership function), is 1 and all others are zero. As the error changes, the degree of certainty changes and other measures of μ have non-zero values. Thus, the errors are encoded by the degree of certainty of their error bounds.

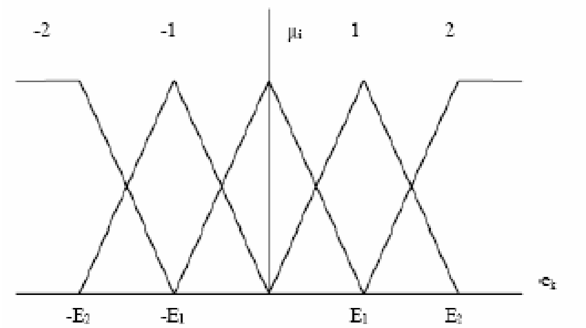


Figure 2. Membership Functions for Fuzzy Logic

Table 1. Rule Table for Fuzzy Logic

OUTPUT		"change in error"				
"error"		**2**	**1**	**0**	**-1**	**-2**
	2	2	2	2	1	0
	1	2	2	1	0	-1
	0	2	1	0	-1	-2
	-1	1	0	-1	-2	-2
	-2	0	-1	-2	-2	-2

The values for the error bounds (E_1, E_2) can be determined using the center-clustering techniques on crash data. Likewise, input membership functions are determined for the change in error. For five error input membership functions and five change-in-error input membership functions, twenty five rules result as seen in Table 1.

Any membership function with a non-zero degree of certainty is said to be 'on' and the corresponding rule is also active [16], [17]. If both the error and change in error were small enough to be within the smallest error bounds (-E_1 to + E_1 in Figure 2), the linguistic rule is considered as follows: If *e* is zero and change in *e* is zero then, correction is zero.

The certainty of the premise, *i*, is given by:

(1) $\mu_i = \min(\mu_{e0}, \mu_{\Delta e0})$

In general, the rules are given as:

(2) If $\tilde{\mu}_{ei}$ is A_{ei}^{j} and $\tilde{\mu}_{\Delta ei}$ is $A_{\Delta el}^{k}$,
then $\varepsilon_i = g_i(\bullet)$ and $\dot{\boldsymbol{\varepsilon}}_i = h_i(\bullet)$

The symbol "•" simply indicates the AND argument. In QFLASP-B, the quaternion error is first reduced to the error in Euler angles:

$$\vec{\varepsilon}_q \rightarrow \{\varepsilon_\phi, \varepsilon_\theta, \varepsilon_\varphi\} \quad (21)$$

The rules of Table 1 are then applied to each Euler angle error. The output correction for each Euler angle and Euler rate is calculated using a center-of-gravity method:

$$\hat{\varepsilon}_{eulerangle} = \frac{\sum_{i=1}^{R} g_i \mu_i}{\sum_{i=1}^{R} \mu_i}, \quad \dot{\hat{\varepsilon}}_{eulerangle} = \frac{\sum_{i=1}^{R} h_i \mu_i}{\sum_{i=1}^{R} \mu_i} \quad (22)$$

Corrections to the body rates can then be determined. To apply quaternion corrections, the estimated error quaternion must be reconstructed:

$$\vec{\varepsilon}_q \leftarrow \{\varepsilon_\phi, \varepsilon_\theta, \varepsilon_\varphi\} \quad (23)$$

These corrections are then applied to the quaternion to remove quaternion error. Once the attitude is determined, angles and rate can be substituted into equation (20). Equation (20) can be integrated to calculate the velocity and position. It is noted that the Fuzzy logic approach discussed here is generic and can be extended to minimize accelerometer systemic errors.

While similar results to the QFLASP-B can be obtained using a Kalman Filter, the operational software overhead is considerable. In our own tests, the Kalman Filter took 3.5 ms to run per iteration, while QFLASP-B took under 1 ms per iteration on a Texas Instrument C33 DSP with a clock speed of 60 MHz. Similarly, the Kalman Filter code required memory of nearly 10,000 words, while the QFLASP-B was under 3,000 words. Both requirements were driven in the Kalman Filter by the matrix inversion, which is absent in the QFLASP-B.

Simulation and Experimental Results

Here, the authors tested the QFALSP-B algorithm through ADAMS-LifeMOD simulations. In these test cases, QFLASP-B performance for head-orientation computation and torso-orientation computation in a frontal crash situation was investigated. The forward kinematics problem was posed and solved in ADAMS [18] that gives body rates and accelerations. These body rates and accelerations were fed into QFLASP in order to solve the inverse kinematics problem. These simulations will help to ensure that:

1. QFLASP-B switches are working properly. There is no time delay in operating switches. A delay in switching would result in inaccurate or incorrect solutions.
2. QFALSP does not encounter singularities. The advantage of QFLASP-B over FLASP-Euler angle formulation is that it can handle 90° pitch situations. Unfortunately, the computation is time-consuming and may introduce group delay that would corrupt the solution.
3. At this preliminary stage, it is not possible conduct to extensive lab testing that would validate QFLASP-B for all possible crash scenarios. It is anticipated that these simulations will reveal problems with QFLASP-B and help tune the algorithm better.

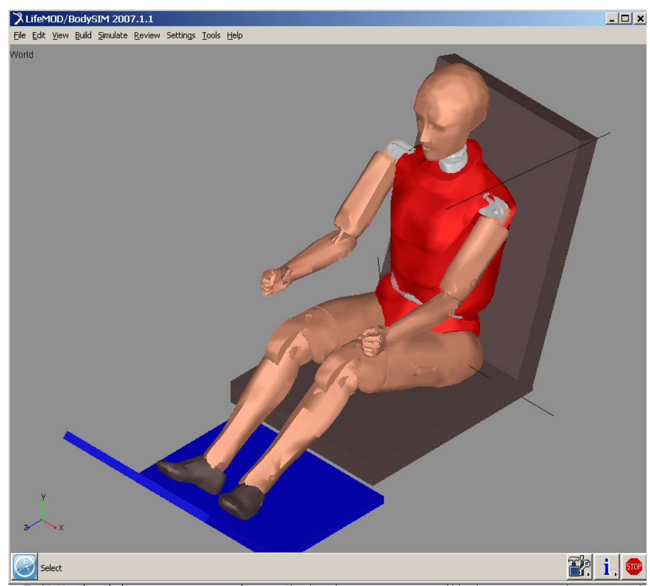


Figure 3. ADAMS-LifeMOD Setup for virtual crash testing

It was noted that the forward dynamics data can be corrupted using gyro, accelerometer-bias models so that this dataset would be very close to experimental data. This corrupted data can be fed into QFLASP-B to evaluate the effectiveness of the algorithm. For this sample simulation, the dummy was postured as an occupant driving the car with 3-point seat belts attached (refer to Figure 3). A translational joint was created between the ground and car seat to simulate impact (standard SAE shock pulse). An equilibrium analysis was carried out so that the model settles under the action of gravity.

An appropriate coordinate transformation matrix was used to preprocess the head angular rate (shown in Figure 4) and head acceleration data obtained from ADAMS simulations before feeding them to QFLASP-B. Head angular velocity in body coordinates is shown in Figure 4. It is noted that ω_x reaches a maximum value of 1500 deg/s. The head orientations computed by QFLASP-B from raw accelerometer and gyro data are shown in Figure 5. It can be observed in Figure 5 that the forward ADAMS attitude solution (obtained from MSC-ADAMS-LifeMod inertial marker) matches quite closely with the inverse QFLASP solution.

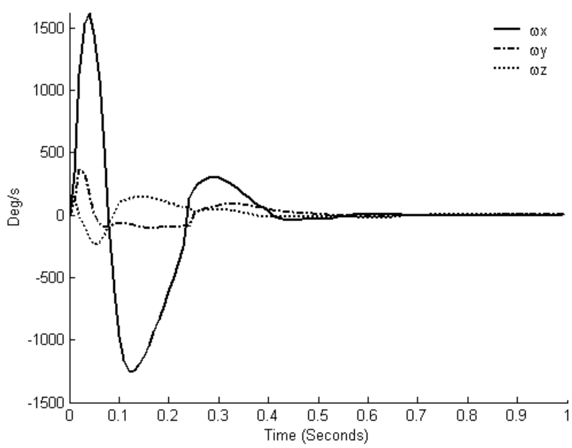


Figure 4. Head Angular Velocity in body frame

In the second simulation, torso response is evaluated in a frontal crash. As before, the dummy was constrained by a 3-point lap shoulder belt and a standard SAE shock pulse was applied. Central torso body accelerations about the x, y and x axes are plotted in Figure 6(a). Central Torso body angular velocities are plotted in Figure 6(b). The attitude solution is presented in Figure 6(c). It should be noted that due to lap-shoulder belts, the central torso motion is restricted. The body accelerations and body rates obtained from ADAMS-LifeMod simulations were fed into QFLASP-B to get torso orientations in inertial coordinates.

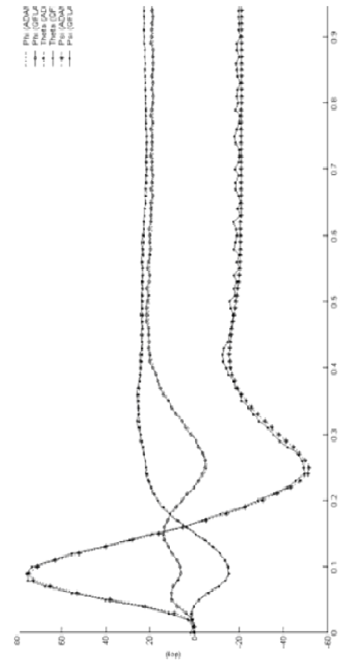
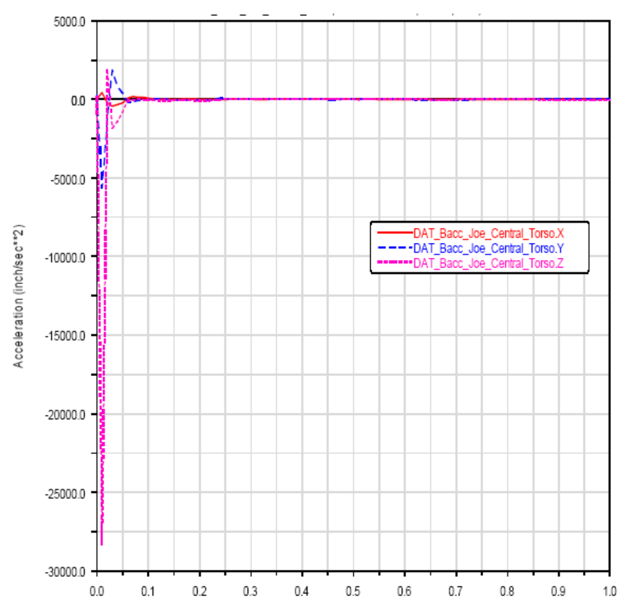
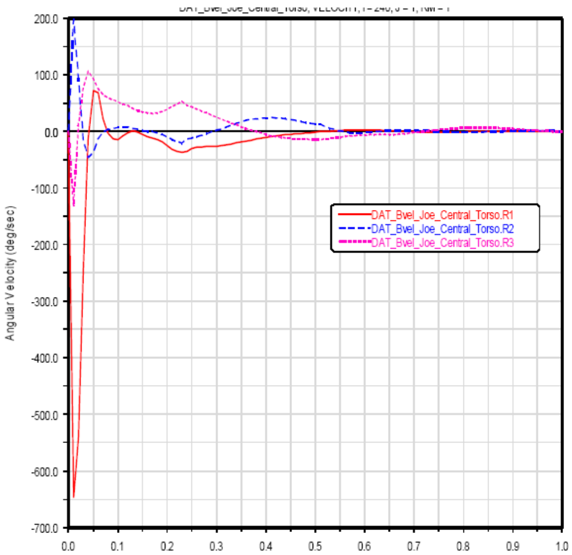


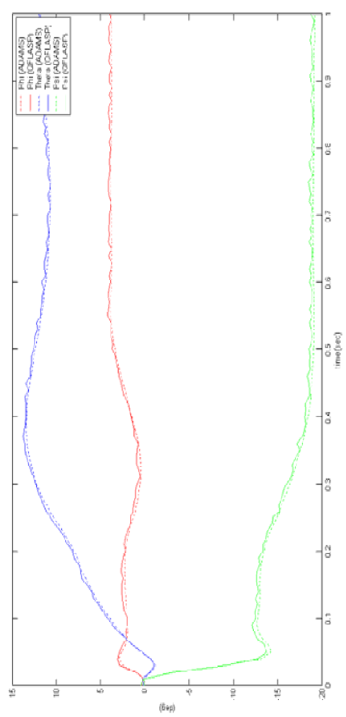
Figure 5. Head Inertial Forward Kinematics- ADAMS solution (indicated by dotted lines) and Inverse Kinematics-QFLASP Solution (indicated by solid lines).



a) Central Torso Body Accelerations vs. time (seconds)



b) Central Torso Body Angular Velocity vs. time (seconds), (R1-rotation about x, R2-rotation about y, R3-rotation about z axis)



c) Central Torso Inertial Forward Kinematics- ADAMS solution (dotted line) and Inverse Kinematics-QFLASP Solution (solid line).

Figure 6. Central Torso Accelerations, Body Angular velocity and inertial solution IMU Coordinates)

It should also be noted that the ADAMS solution sensed by a marker in an inertial frame matches quite closely to the attitude solutions computed by QFLASP-B, as shown in Figure 6(c).

Experimental Validation

In preliminary studies, the algorithm was tested for head kinematics. The purpose of this test was to evaluate head-restraint responses. There was about 20 msec of pre-crash data (about 250 points), which was used for bias capture. The test was done on a Hybrid III 50th percentile dummy with NAP and angular sensors. The advantage of such a configuration is that it is possible to compute head orientations using the NAP algorithm [1] and also acceleration and rate data can be fed into QFLASP-B. Thus, head orientations can be computed with two different techniques. The setup with sensor-mounting locations is shown in Figure 6. The dummy was subjected to standard SAE crash pulses and the raw sensor data in body coordinate system is shown in Figure 7. It is important to note that for meaningful results, the IMU coordinate system (at the CG of the head) should be mapped to the SAE coordinate system.

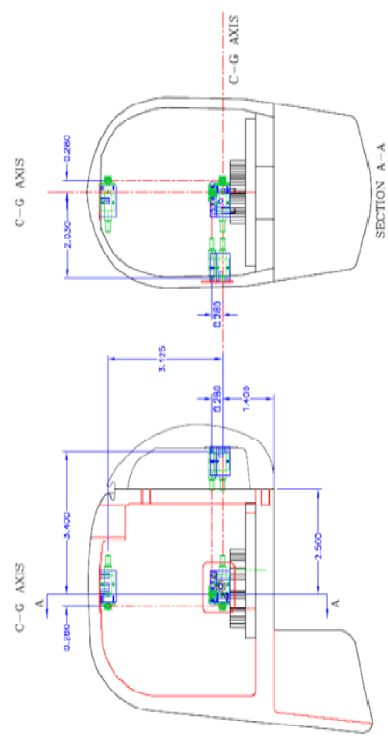


Figure 6. Setup for Head Kinematics Test (sensor mountings locations shown in green)

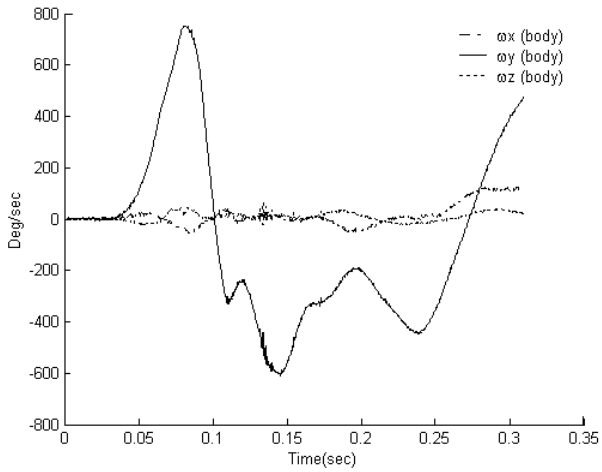


Figure 7. Raw Rate Sensor Data in Body Coordinates

An appropriate coordinate transformation matrix was used to preprocess the data before feeding them into QFLASP-B. In Figure 7, it can be observed that rates about the 'y' axis are very high at about 800 deg/s. The orientations computed by QFLASP-B are shown in Figure 8. It can be noted that pitch varies from +20° to -30° (rebound motion). However, roll and yaw are within 5°. These results compare favorably

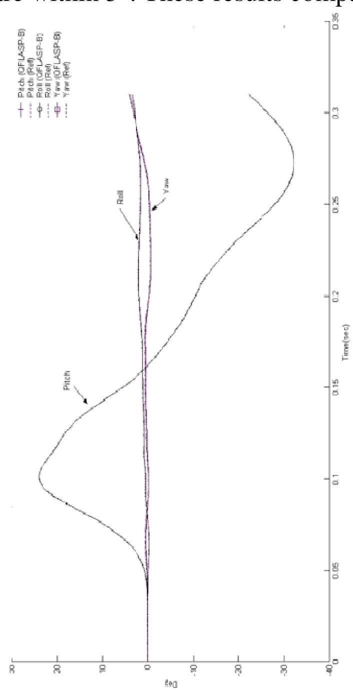


Figure 8. Attitude Solution in Head Restraint Test NAP Solution (indicated by dotted lines) and QFLASP-B Solution (indicated by solid lines)

with the reference NAP solution shown in Figure 8. However, due to less computation overhead, the speed of execution of QFLASP-B is much higher and QFLASP-B uses body accelerations for slaving (or to correct attitude solution using accelerometer data). Therefore, unlike the NAP processing algorithm, QFLASP-B can be operated in runtime for a longer duration or on a much cheaper DSP platform, if required. Other kinematic parameters such as angular accelerations, linear accelerations and inertial angular velocity can be easily derived using this approach, which can be used to compute injury measurements. It can be seen that this inertial measurement allows for computing relative orientations of various body parts, such as head rotation with respect to neck, in a fixed reference frame.

Discussion and Conclusions

In this study, the authors presented a novel approach for sensing dummy kinematics in crash events using inertial measurement via Fuzzy logic. Sensing of dummy kinematic parameters in a crash event is crucial for evaluating the crashworthiness of vehicles. These kinematic parameters were used to compute various injury parameters, to understand the severity of injuries, to study the effectiveness of seat belts and airbags, and other occupant safety devices. The inertial-sensing approach discussed here is based on sensing rates and accelerations in 3 mutually perpendicular directions and using a Fuzzy-Logic-based algorithm for computing inverse kinematic inertial solutions. This superior signal-processing algorithm compensates for sensor errors like noise and drift present in typical low-cost MEMs sensors and provides equally accurate solutions normally obtained by expensive testing methods/sensor suites. This quaternion-based approach is free from singularities at 90° and, unlike the Kalman filter, does not involve matrix inversions. The hardware and software aspects of inertial sensing along with simulations and preliminary experimental results were also discussed. In simulations, forward-kinematics problems were posed and solved in MSC -ADAMS to obtain body rates and accelerations. These accelerations and rates were fed into QFLASP to obtain an inverse kinematic inertial solution. Two simulation cases, head-orientation calculation and torso-orientation calculation, were presented. In both cases, the MSC-ADAMS solution obtained via a marker in an inertial frame matches very closely with the QFLASP solution.

In preliminary experimental tests, the QFLASP algorithm was tested to compute head orientation and compared against the solution computed by a standard NAP sensor suit. The NAP solution and QFLASP solution matched quite well. Currently, efforts are underway to test QFLASP in a variety of crash situations. QFLASP can be implemented on a low-cost DSP at much higher update rates. It is anticipated that this Inertial Tracking/Measurement approach will enable test engineers to use low-cost MEMs sensors for crash testing and provide an inexpensive alternative for measuring kinematic parameters in a crash event.

Acknowledgments

The authors thank Dr. Michael Greene and Mr. Victor Trent of Archangel Systems for their help in this project. Support from MSC Software and the US Department of Transportation is also gratefully acknowledgement.

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