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*BIOMECHANICS RESEARCH: Experimental and Computational, Proceedings of the Twenty Sixth International Workshop.*

# Use of a Kalman Filter to Improve the Estimation of ATD Response During Impact

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## ABSTRACT

*A method for determining velocity in biomechanical impact experiments on human surrogates is presented. It employs a Kalman Filter to combine experimental acceleration and displacement measurements along with kinematic models of the human surrogate and statistics of the experimental noise to derive an estimate of the velocity in a maximum likelihood sense. Results from two velocity levels, less than 1 m/s and over 10m/s, are presented to illustrate the broad range of application of this approach. The velocity of deflection of an anthropomorphic test device (ATD) in two airbag related cases are presented: an out of position child ATD and an in position adult advanced ATD. The results indicate that the problems associated with attempting to obtain velocity from either acceleration or displacement can be eliminated or significantly reduced. The inherent noise from unfiltered differentiation of displacement, the loss of information from standard filtering procedures and the velocity drift from low frequency noise when integration is used on acceleration are eliminated or significantly reduced.*

## INTRODUCTION

Obtaining the response of a human surrogate to an impact event typically requires measurement of certain phenomena (acceleration and displacement) and estimation of others (velocity). Velocity is an important parameter to measure in certain impact tests. For example, the chest cavity and associated internal organs represents a viscous environment. Forces on internal organs can be a function of both chest deflection and their velocity of deflection relative to their fluid surroundings. An accurate way of estimating chest velocities, such as the velocity of the sternum relative to the spine, is necessary in order to assess the injury potential [1-4].

Velocity is typically derived from accelerometers, displacement transducers or film analysis by means of various algorithms. There are few sensors that provide direct measurement of velocity. Furthermore, there are no direct measurement velocity transducers currently used in standard vehicle crash applications. Each commonly employed method of estimating velocity from related phenomena is subject to interpretation and measurement noise. Numerical differentiation of displacement data is inherently noisy and requires application of filtering. Numerical integration of accelerometer data is subject to drift, time shifting and emphasizes any steady state errors that may exist in the system. Film analysis is labor intensive and cannot capture high speed events.

## STATE MODELING TECHNIQUES

State models are a way to estimate the dynamics of a system. State models are common tools used in modern control theory and have been applied in numerous aircraft systems and, more recently, automotive systems, including emissions control algorithms. A state characterizes a dynamic system at some point in time (e.g., position and its time derivatives). An example of a state is the rectilinear kinematics of a particle, x:

$$\mathbf{x} = \begin{bmatrix} x \\ \dot{x} \\ \ddot{x} \end{bmatrix} \tag{1}$$

The column of observations suggests that the state is a vector. The state model is typically expressed in vector/matrix formulations.

The state model is a description of how the dynamics of a system is propagated over time. The modeling of a system involves determining the state transition equations. Typically, these are taken from equations of motions based on the kinematics (motion) or the kinetics (force/motion relationships) of a system. Each state can be related to the other states by a relationship from an equation of motion or an approximation made from empirical observations of a system. A simple state model for the rectilinear kinematics of a particle is given by:

$$\begin{aligned} x_1 &= x = \text{ Position} \\ x_2 &= \dot{x}_1 = \text{Velocity} \\ x_3 &= \dot{x}_2 = \text{Acceleration} \\ x_4 &= \dot{x}_3 = \text{ "Jerk"} \end{aligned} \tag{2}$$

The state of the system appears as the variables x1 … x4. The equations of motion that describe the interrelationship of these variables comprise the state transition model. The state model is the combination of the state transition (how position is related to velocity, etc.), any deterministic input (such as an actuator that could drive a component from one position to the next) and the noises that corrupt the states (the system or process noise). A complete state model is shown below:

$$\dot{\mathbf{x}} = \mathbf{Ax} + \mathbf{Bu} + \mathbf{Gw} \tag{3}$$

The state change is determined by the state transition model (the product of A and x), the deterministic input, u, and the effect of system noise, w. B and G are used to scale the input and the noise to match the dimensions of the state. The system noise is a way to describe or compensate for systems that are poorly understood or inadequately modeled. A state model that is corrupted by system noise with a large standard deviation is one that does not have a good dynamic model to describe its performance.

The states can be measured directly or related indirectly to measurements made on the system. An example would be the relationship between the state of a vehicle (position, velocity and acceleration) and a measured phenomenon of motion (acceleration). A typical model for measurements in a state model format would be:

$$\mathbf{z} = \mathbf{H}\mathbf{x} + \mathbf{v} \tag{4}$$

The measured phenomena (z) are related to the state (x) by a transformation, H. The observer sees measurements of the state that are corrupted by measurement noise, v. The measurement noise is a way of describing the disturbances that typically corrupt a sensor (mechanical or electrical interference). A measurement model corrupted by a large standard deviation measurement noise is one that has sensors providing data subject to significant interference.

## KALMAN FILTER ESTIMATORS

Kalman filters are tools for estimating the states of a dynamic system from available data. Kalman filters are applied to problems where noisy, uncertain measurements are taken from a dynamic system and states must be estimated. These filters or estimators use a standard algorithm for state estimation that is customized based on the state transition and measurement model that applies to a specific system. These estimators provide a powerful (and possibly optimal, under certain conditions) means of dealing with:

- Uncertain systems (systems that are not well understood and corrupted with system or process noise)
- Uncertain measurements (observations that are corrupted by measurement noise) [5,6].

A Kalman Filter can be applied in real time or as a way of post processing measurements. Typical applications for Kalman Filters include:

- ICBM Systems: Noisy measurements of missile acceleration are used in conjunction with a ballistic model to guide a missile.
- Ground to Air Defense: Limited, noisy radar measurements are used to track a target (e.g., Patriot)
- Aircraft Navigation: Locations are estimated based on speed, attitude and heading [6].

The Kalman Filter is a well-documented algorithm for continuous and digital systems. There are several modeling environments that directly support its implementation (e.g., MATLAB, Simulink and others). The process is illustrated in the flowchart shown in Figure 1 [7]:

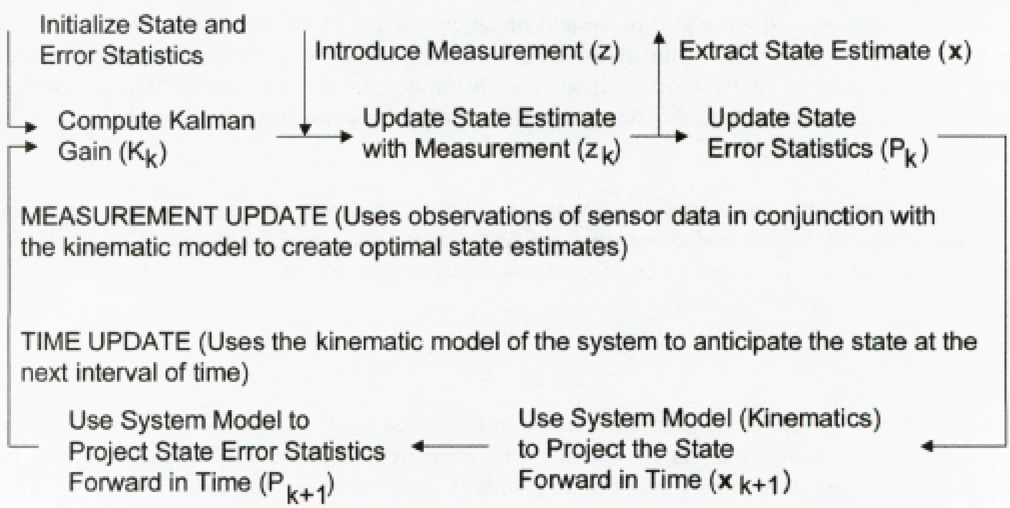


**Figure 1.** Kalman Filter Algorithm

The Kalman Filter operates recursively with a new measurement and a new estimate of the system dynamics being used to update the state at each time step. The input to the system is the measurements. The output is the estimate of the state at each time step.

Implementing the algorithm is a straightforward procedure. However, significant engineering insight is necessary to apply the algorithm to a specific system. There are several key elements to the implementation of a successful Kalman Filter:

- A reasonable state model must be created. These result from an understanding of the dynamics of the system and are generally traceable to the first principles of physics. Some models are widely known for simple systems (e.g., a particle subject to a constant acceleration).

- The system model must be "tuned." The tuning process requires an understanding of the system or process noise. The variance of the system noise needs to be selected. A large magnitude noise indicates that the state model is not very accurate. This does not necessarily mean that the Kalman Filter will not provide good state estimates. The Kalman Filter is capable of producing accurate state estimates if the system noise is properly characterized. This will frequently require experimental trials to effectively test the model accuracy. The amount the deviation between the actual system performance is stationary (i.e., does not vary significantly over time), the Kalman Filter can apply measurements to create very good state estimates.

- The measurement model must be tuned. The process requires an understanding the measurement noise. The variance of the measurement noise must be selected. A large magnitude measurement noise indicates that the sensors used to observe the system are highly corrupted. As with system noise, this does not meet that good estimates cannot be derived from the Kalman Filter. Kalman Filter estimators can produce highly accurate state estimates provided that the sensors are well understood and are subject to noise that has observable statistics.

Generally, the tuning of the measurement model is much easier than the system model because the sensors are generally well understood devices and experimental techniques exist to provide accurate characterizations of sensor performance.

## ESTIMATION OF ATD RESPONSE

One potential application for the Kalman Filter approach is to estimate the velocities in the chest cavity of an ATD ("crash test dummy"). The chest velocity is difficult to accurately derive from sensor data collected from a typical test. Typically accepted instrumentation for estimating velocities in the chest of an ATD is:

- accelerometers mounted to the sternum and spine
- displacement transducers mounted between the sternum and spine

Each of these transducers is indirectly related to chest velocities. Current chest velocity estimation techniques typically use:

- numerical integration of the difference between the chest and spine acceleration measurement channels
- numerical differentiation of the displacement measurement channel

Each of these approaches is problematic. The numerical integration is prone to drift, time shifting and accumulation of steady state error (the chest motion has stopped; yet, the velocity estimate shows motion is still occurring). The numerical differentiation, like virtually all numerical derivatives, is highly noisy.

The following presents two examples of the types of faults that result from these numerical estimates. The examples are selected to represent extremes in conditions. The first example is based on an airbag deployment on a $50^{th}$ Percentile Male NHTSA Advanced ATD (TAD). This is a standard in-position test under the conditions of a standard 30-MPH crash test. This example is characterized by small deflections; consequently, the full-scale gain is set very high, resulting in a noisy signal. The second example is an out-of-position test with a 3-year-old ATD brought in contact with the airbag module while in a static test buck. This example is characterized by very high velocity changes in a small time interval. In each case, the displacement represents motion of the sternum with respect to the spine. The acceleration is the difference of the sternum and spine motion. Filtering of each data set followed SAE J211 guidelines.

## IN-POSITION EXAMPLE

Figures 2 and 3 show the sternum acceleration and displacement for the standard In-Position test. The chest motion begins at about 0.04 seconds. The acceleration profile indicates that the motion of the chest began at approximately 0.04 seconds into the test and that the sternum undergoes significant variations in acceleration during the event. As would be expected in this type of test, the overall deflection of the chest is relatively small.

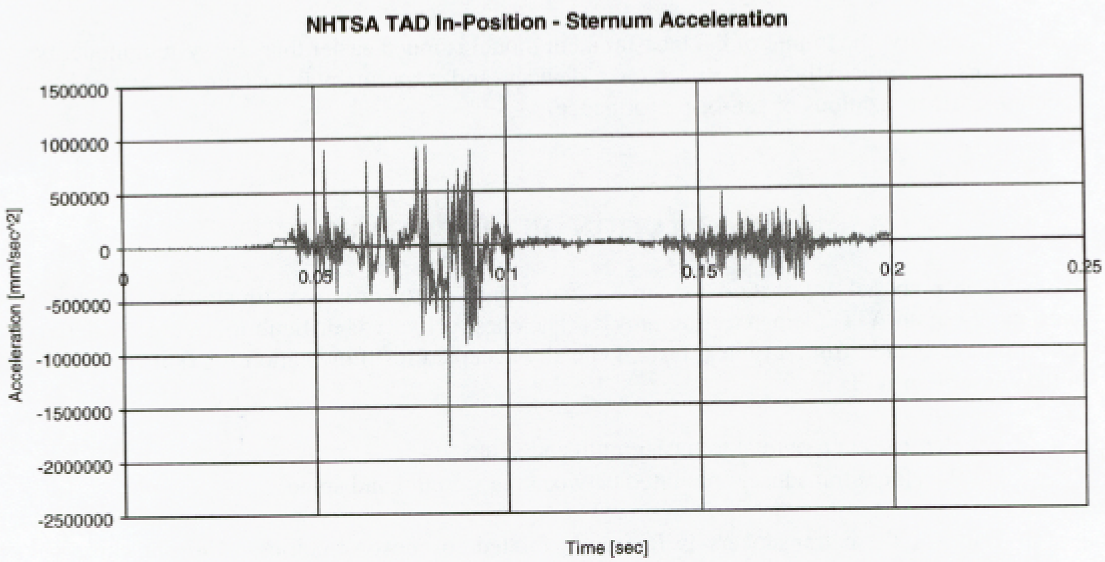


**Figure 2.** Sternum Acceleration

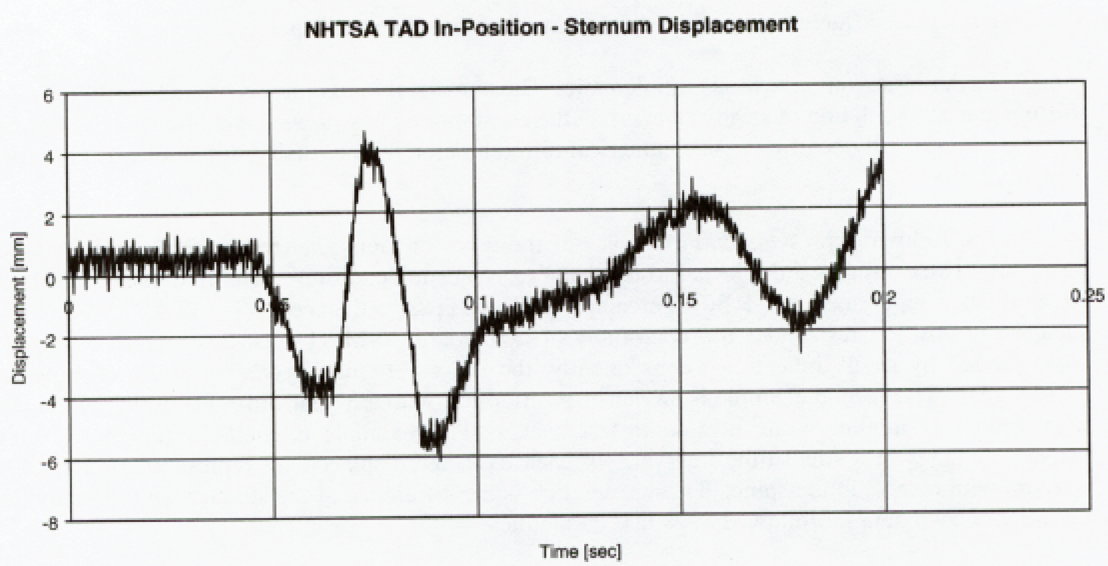


**Figure 3.** Sternum Displacement

The typical estimates of velocity extracted from the accelerometer and displacement transducer are illustrated in Figure 4.

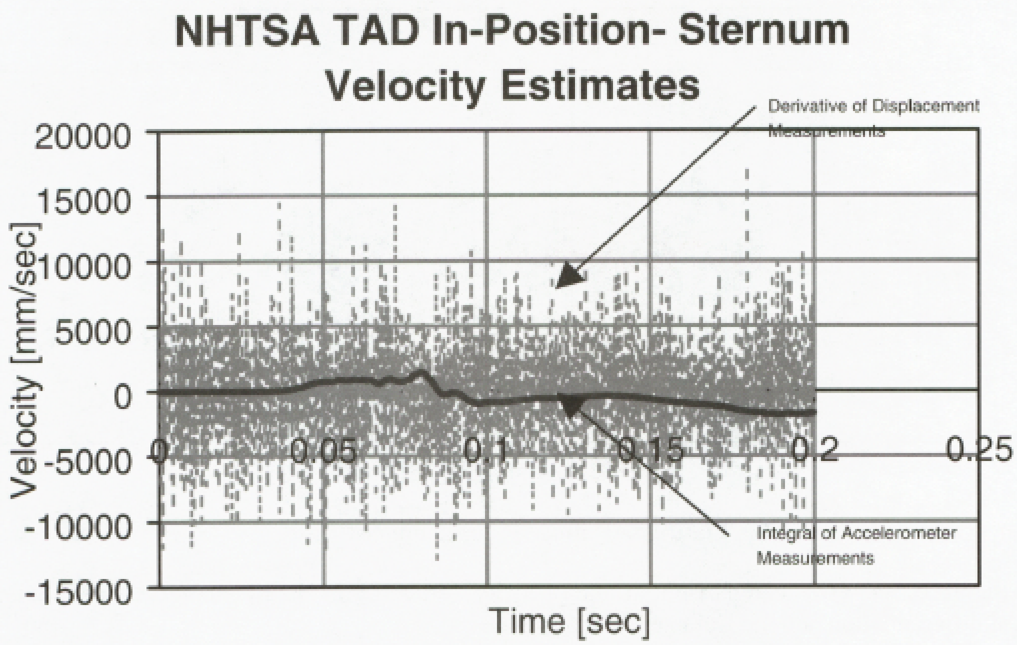


**Figure 4.** Velocity Comparisons

The derivative of the displacement shows a large signal to noise ratio that basically occludes a reasonable estimate of velocity. The integral of acceleration exhibits significant accumulated error over time

Various ad hoc strategies can be employed to correct the errors in the estimates of velocity based on displacement and acceleration measurements. Some common approaches include applying low pass filters to the noisy velocity measurements and using a moving average smoothing technique. The low pass filter approach requires the judicious selection of a break frequencies and number of poles. The moving average approach is highly dependent on the interval selected for the averaging. In both cases, parameter selection is subjective and results are inevitably corrupted by time shifts and attenuation of important information. Ultimately, these strategies are difficult to trace to first principles and find consensus among various strategists.

## KALMAN FILTER APPROACH TO VELOCITY ESTIMATION

A Kalman Filter approach has been applied to the estimation of ATD response. A state model was formulated that consisted of the equations of motion for position and the three corresponding time derivatives (velocity, acceleration and jerk). This model was used in conjunction with observations of acceleration and position to produce estimates of the state (position, velocity and acceleration). The resulting estimates of velocity were compared to the estimates derived from numerical integration and differentiation of transducer measurements.

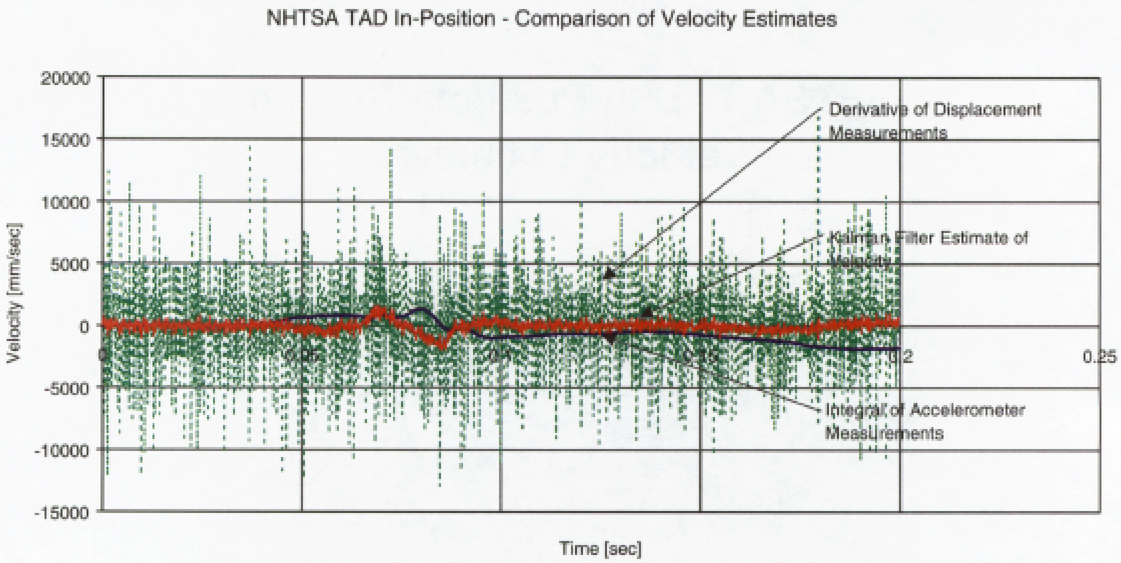


**Figure 5.** Kalman Filter Estimates

Figure 5 shows a comparison of the velocity estimates made by numerical integration, numerical differentiation and the Kalman Filter.

The comparison of three estimation techniques shows the limitations of the numerical differentiation and integration techniques. The Kalman filter estimates clearly tracks the centroid of the derivative estimate, changing direction in a synchronized fashion with the derivative. The derivative does not tend to mask the underlying dynamics of the velocity profile and the Kalman filter estimate clearly tracks them without time shifts. The signal to noise ratio of the Kalman filter estimate is nearly an order of magnitude smaller than that exhibited by the numerical differentiation technique. The effects of the time shift and error accumulations in the numerical integration technique are also shown clearly. The large changes in direction occur in the profile between 0.06 and 0.10 seconds are time shifted by nearly 0.02 seconds in the integral estimate.

The comparisons are open to significant debate since there is no "ground truth" for the velocity. There is no direct measurement of velocity available to use as a baseline. Fortunately, there is one additional comparison that can be made to help provide some validity to the Kalman Filter estimate. The Kalman Filter also produces estimates of position and acceleration (adjusted by the state model for the influence of process and measurement noise) as well as the velocity. These three kinematic quantities can be compared to illustrate the effectiveness of the Kalman Filter approach as shown in Figure 6.

The position and velocity are scaled so that they can be compared on the same graph. The time phasing of the kinematics follows basic principles of physics. The profiles exhibit rapidly changing kinematics between 0.05 and 0.10 seconds. During this interval, when the displacement is maximum, the velocity crosses zero (the time axis). Similarly, when the velocity is maximum or minimum, the acceleration crosses zero. These observations help confirm the proper time phasing of the three kinematic quantities. Similar analysis can be done that will confirm the proper magnitudes of the quantities (using numerical integration of the acceleration and comparing the magnitude of the result to the estimated velocity). These comparisons are also favorable.

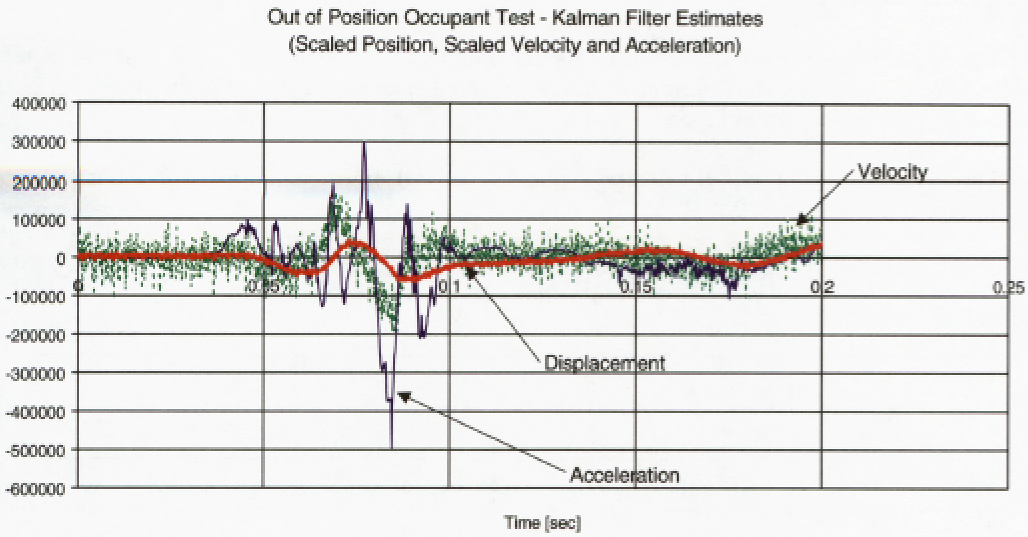


**Figure 6.** Kinematic Comparisons

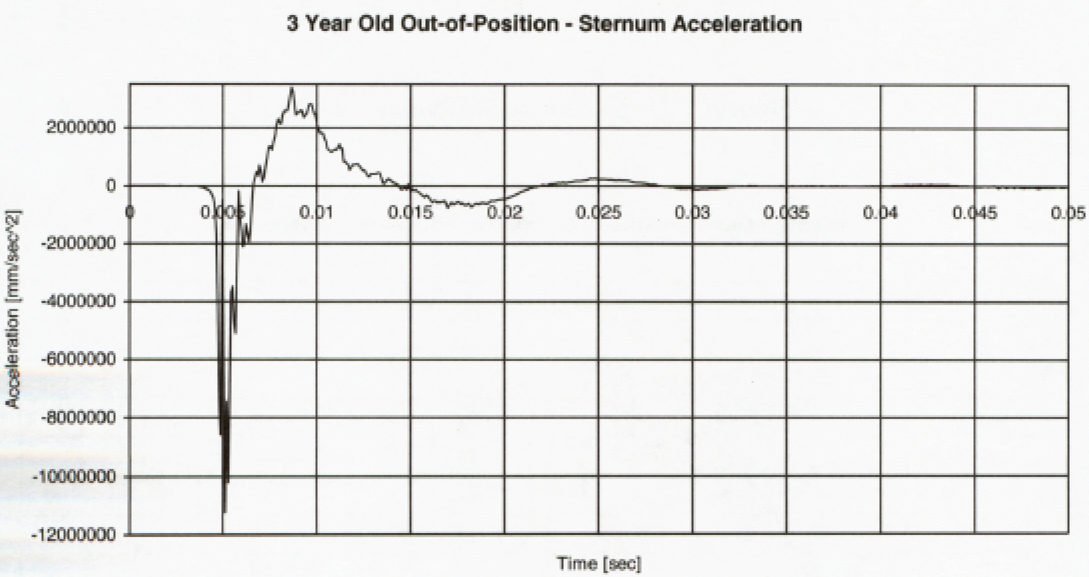


**Figure7 .** Acceleration Measurement

## OUT-OF-POSITION TEST

The technique was also applied to the demanding dynamic conditions of an Out-of-Position test with a 3-Year-Old ATD. The sternum acceleration and displacement (found in the same way as in the In-Position test) are shown in Figures 7 and 8.

The comparisons of chest velocity estimates derived from numerical differentiation and integration are shown in Figure 9.

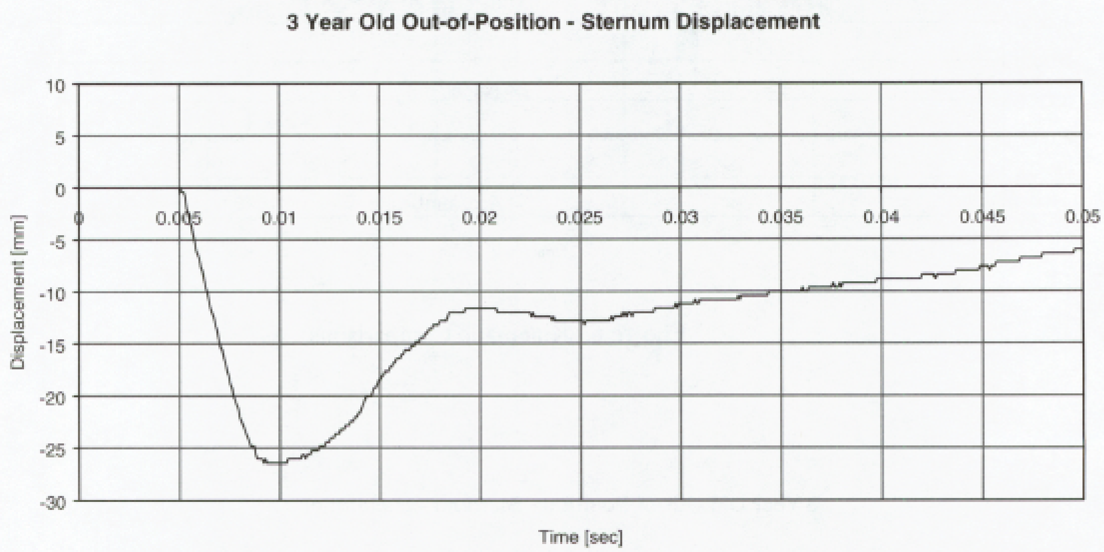


**Figure 7.** Displacement Measurement

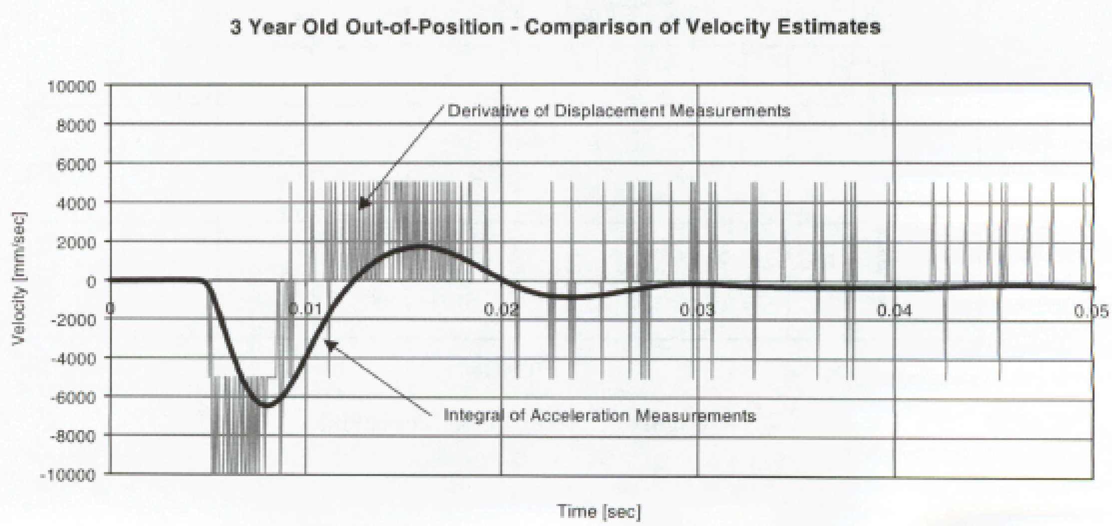


**Figure 8.** Velocity Comparisons

The corresponding Kalman Filter estimates of displacement, velocity and acceleration are shown in Figure 10. As is the case with the In-Position test, the kinematic quantities have the appropriate time phasing to make them internally consistent.

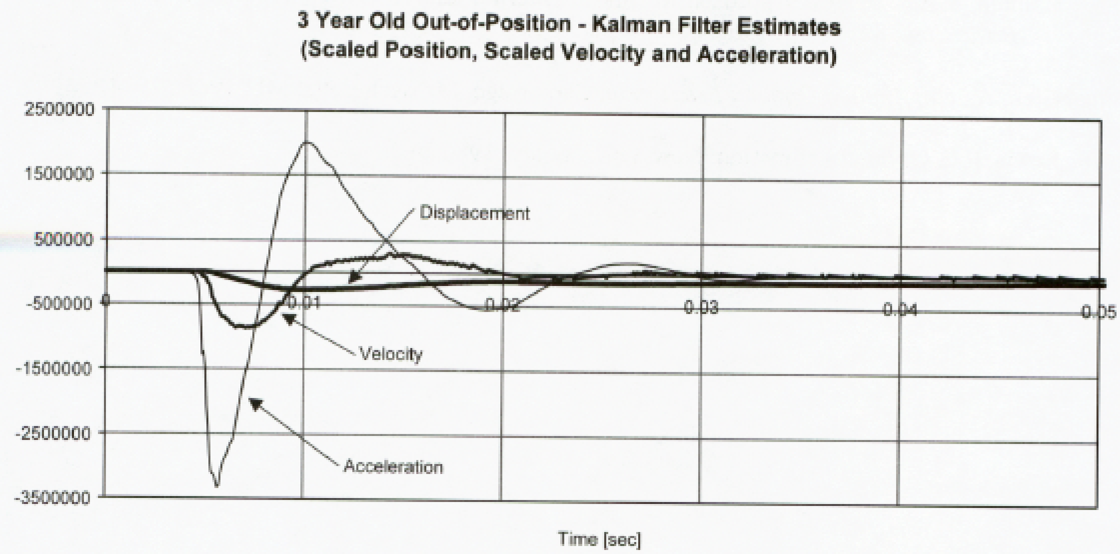


**Figure 9**. Kinematic Comparisons

## CONCLUSION

The state model approach offers an accurate means of estimating quantities related to ATD response, such as velocity, that are difficult to measure directly. The state model/Kalman Filter approach can provide a standardized approach to estimating velocities and other dynamic responses. The standardization or wide acceptance could be made possible by the treaceability of the approach to the first principles. Ultimately, this approach could provide a way to gain a better understanding of the response of an ATD to a crash event and the associated mechanisms of injury.

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