APPLICATION OF EVIDENCE ACCUMULATION BASED ON ESTIMATION THEORY AND HUMAN PSYCHOLOGY FOR AUTOMOTIVE AIRBAG SUPPRESSION

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Abstract: The traditional D-S conditioning is based on a collection of 'experts' inputting their evidence and accumulating the beliefs. Researchers have often adopted this same mechanism for integrating evidence from single sources of evidence over time, such as seen in sensor networks. The traditional D-S conditioning ensures the order of inputs does not matter. While this is sensible for a collection of experts we propose that it is not suitable for a single input providing streams of evidence. Research in psychology show order of integration of evidence does matter, and depending on the application humans have a preference for recency or primacy. Estimation theory provides frameworks for analyzing data over time, and recently some researchers have proposed integrating evidence in an estimation-inspired manner. We then propose a Kalman-filter based approach for integrating temporal streams of evidence from a single sensor. We then propose the system uncertainty be modeled by the conflict defined by Dempster. We then define a real-time evidence accumulation system for airbag suppression and demonstrate that the Kalman filter-based approach indeed out-performs Dempster-Shafer based evidence accumulation.

1 INTRODUCTION

It has been recognized in cognitive psychology research that a key aspect of belief updating is its sequential nature. There has likewise been significant research in the artificial intelligence community with respect to evidential reasoning, with the most common approaches being Bayesian and Dempster-Shafer (D-S), but other methods such as Transferrable Belief Model, Possibility Theory, Fuzzy Logic, etc. also playing critical roles. This paper will use Dempster-Shafer as its foundation. There are three key areas where the existing research in evidential reasoning has differed significantly from the findings in human cognition, (i) order effects, (ii) evidence impact reduction in long evidence streams, and (iii) evidence evaluation versus estimation. As high performance real time sensors, particularly imaging sensors become more pervasive, it is time to relook at the mechanisms of evidence accumulation and belief updating from temporal streams of sensor data.

The first issue, namely that of order independence is not found to exist in human reasoning, and there are definite situations when order-effects are present, either in the form of recency preference or primacy preferences (Hogarth and Einhorn, 1992); (Wang et al., 1999); (McKenzie et al., 2002); (Baratgin and Politzer, 2007). Most traditional approaches such as Dempster-Shafer ensure order independence, and there is no mechanism to support when order dependence is important.

The second issue which demands another look is that of how to integrate evidence over long streams of data. In human cognition there is clear research evidence that the impact on new information should reduce as more evidence is gathered, whereas the common approaches of Bayes and D-S weight the entire history equally with the most recent input.

The third issue related to human cognition is based on what cognitive researchers call encoding (Hogarth and Einhorn, 1992). In human evidential reasoning there are two approaches, evaluation and estimation. Evaluation is a process in which the reasoning tasks tend to be formulated into a true-false framework and evidence in encoded positive or negative with relation to a hypothesis (it either supports or refutes). Evaluative reasoning is identical to the Bayes formulation for combining

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evidence. Estimation tasks, however, are additive in nature and assess 'how much evidence is to be allocated to a belief'(Hogarth and Einhorn, 1992). Cognitive researchers have found that 'estimation may be more frequently used than evaluation', whereas artificial reasoning systems tend to rely on the evaluative approaches.

A final issue in addition to the three related to human cognition is that of the meaning of data independence in evidence combining. The clarity of when data is independent is different when integrating evidence across sensors or experts compared to when integrating evidence temporally from individual sensors. Liu and Hong recall that Dempster was very clear where he stated: "Different measurements by different observations on different equipment would often be regarded as independent" (Liu and Hong, 2000). Thus there should be a distinction between these two types of integration yet the distinction has generally not been widely recognized or exploited in the literature to date. We propose there is a need for a distinction between traditional statistical independence and the stronger independence proposed by Dempster, which we term Evidential Independence. For temporal integration of data within single sensors, statistical independence is to be expected, however evidential independence should not be expected. This distinction in the types of independence requires different a approaches for integrating evidence over time from a single sensor.

The purpose of this paper is to review evidence combination approaches and show the need for an alternative approach that provides for temporal integration of information from a single sensor. We then propose a framework for such a system devised from first-principles of Kalman filtering where the concept of evidence conflict defined by Dempster plays a critical role in managing the adaptive filter gain. We then apply the algorithm to an interesting real-world automotive airbag suppression problem and demonstrate that the Kalman approach has superior performance to a traditional discounted Dempster-Shafer approach.

2 EXISTING APPROACHES TO COMBINING TEMPORAL STREAMS OF EVIDENCE

Dempster's Rule of Combination has been extended to process a temporal stream of sensor inputs by viewing m2(a) "not as sensor Sj's observation, but instead as the previously combined observations. Wu et al. propose extending Dempster-Shafer by weighting the masses in the computation accordingly (Wu et al., 2003):

$$m_1 \oplus m_2(Z) = \frac{\sum_{X \cap Y = Z} w_1 \cdot m_1(X) . w_2 \cdot m_2(Y)}{1 - \sum_{X \cap Y = \phi} w_1 \cdot m_1(X) . w_2 \cdot m_2(Y)}, \qquad (1)$$

where the weights are computed according to:

$$w_i(t) = \sum_{n=0}^{\infty} c_i(t - n \cdot \Delta T) \cdot p^n, \qquad (2)$$

and $c_i(t)$ is either 0 or 1 depending on whether the sensor estimate is correct or not, ΔT is the incoming data sampling rate, and p controls the decay rate of samples being considered. Unfortunately for many classification systems, there is no knowledge of whether the incoming sensor data is correct or note.

Farmer has likewise proposed an extension to Dempster-Shafer based on pre-processing the incoming sensor data based not on reference to correctness, but rather on its credibility in relation to past system beliefs, where incoming probability masses are discounted using (Farmer, 2006):

$$m(A) = \left\{ \begin{array}{c} p \cdot m(A) \ \forall A \in P(\Theta), \text{ where } A \neq \Theta \\ \text{and} \\ p \cdot m(A) + (1-p) \cdot 1, \text{ for } A = \Theta \end{array} \right\}, \qquad (3)$$

where the probability p of the evidence being valid is determined by:

$$p = 1 - \frac{\sum_{P(\Theta)} \left| Bel_{temp} - Bel_{last} \right|}{\sum_{P(\Theta)} Bel_{last}}, \qquad (4)$$

and Bel_{temp} is the beliefs assuming the new information has been integrated, and Bel_{last} is the beliefs prior to the inclusion of the new information.

Once the incoming masses are discounted they are integrated using Dempster's standard rule of combination.

Integration of temporal streams of data sources, such those found in signal processing systems typically employ estimation techniques.

One estimation framework has been developed by Premaratne, et al. where they define belief updating according to (Premaratne et al., 2007):

$$Bel_{k+1}(B_1) = \alpha_k \cdot Bel_k(B_1) + \beta_k \cdot Bel_k(B_1 \mid A), \qquad (5)$$

where the weights are constrained by $\alpha_k + \beta_k = 1$. The weight selection controls the relative importance of new versus historical evidence, thereby providing a mechanism to support primacy and recency; however, the authors did not address the task of weight selection and evolution. We will specifically address these two key aspects of evidence filtering (weight selection and weight evolution) in our proposed approach in Section 5.

Equation (5) exhibits some of the behavior we tend to expect when processing temporal streams of evidence, namely: "…when encountered with the same streaming information continuously, the belief converges to a value decided solely by this incoming information" (Premaratne et al., 2007).

Benferhat, et al. developed an analogy to the Kalman filter for qualitative belief revision within Possibility Theory, where they assume a prediction equation of the simple form, $f(\omega_t) = \omega_{t+1}$ where ω_t is the belief state at time *t*. The estimated possibility for state ω at time t+1 is then (Benferhet et al., 2000):

$$\pi'(\omega) = \Pi_t(f^{-1}(\omega)) = \max_{\omega' = f^{-1}(\omega)} \pi_t(\omega'), \quad (6)$$

and the estimate update is(Dubois & Prade, 1997):

$$\pi_{t+1}(\omega) = \pi'(\omega \mid A, \alpha) = \max(\pi(\omega \mid A), (1-\alpha) * \pi(\omega \mid \overline{A})), \quad (7)$$

where A is the new information provided by the sensors, and α is the necessity measure of the input *A* (a measure of its certainty or error). The $(1-\alpha)$ term reduces the plausibility value $\pi(\omega \mid \overline{A})$, and hence the rankings.

3 BELIEF REVISION IN HUMAN PSYCHOLOGY STUDIES

Hogart and Einhorn (Hogarth and Einhorn, 1992) suggest that the recency effect is more important when messages are inconsistent. This result was also verified by Wang et al. for an interesting Combat Information Center application (Wang et al., 1999). Baratgin and Politzer recently address the issue of updating (dynamic environment) in human decision making and confirm by reviewing numerous studies that "a message has greater contextual effects when it is learnt in the last position" (Baratgin & Politzer, 2007).

For example, in response to their order effect results Hogarth and Einhorn proposed an anchoring and adjustment model to explain these order effects. They developed the following model for belief adjustment (Hogarth and Einhorn, 1992):

$$S_k = S_{k-1} + \alpha S_{k-1}[s(x_k) - R] \quad \text{for } s(x_k) \le R, \quad (8)$$

and

$$S_k = S_{k-1} + \beta(1 - S_{k-1})[s(x_k) - R] \quad \text{for } s(x_k) > R, \quad (9)$$

where S_k is the current level of belief, S_{k-1} is the belief at the last update, $s(x_k)$ is the new evidence input into the system, and α and β are weights to enforce sensitivity towards negative or positive evidence, relative to a reference level of support R. This model also supports decaying impact of evidence through the mechanism where "as information accumulates and as people become more firmly committed to their beliefs, values of α and β would decline in a long series of evidence items" (Hogarth and Einhorn, 1992).

Hogarth and Einhorn noted that the values for the constants of evidence integration, α and β, would change over time to modify the changing impact of new evidence in relation to the aggregated body of evidence up to that point in time (Hogarth and Einhorn, 1992).

4 VIDEO-BASED AIRBAG SUPPRESSION AS A MODEL PROBLEM

Farmer and Reiman developed an interesting system application which can be used to demonstrate the application of evidential stream processing (Farmer and Reiman, 2006). They developed a monocular vision system which viewed the occupant in a passenger vehicle and disabled the airbag if the occupant was a infant or child, or in the case of an adult, if the occupant was leaning too close to the bag for a safe deployment. A diagram of the system concept is provided in Figure 1. The image processing for this system consisted of two parallel paths, one for classification processing and one for track processing. The classification system provided a result at a 0.2 Hz rate.

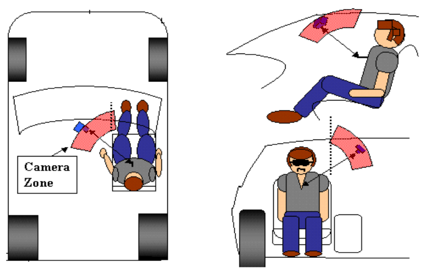

Figure 1: System concept for airbag suppression system.

There are four classes of occupants which comprise the Frame of Discernment: $\Theta = \{$infant, child, adult, empty$\}$. Example images for these classes are shown in Figure 2. As the vehicle drives through the world, the occupant is moving, and there are shadows and light bands moving across the camera field of view that will continuously change the scene the camera is processing. The classification system must integrate this temporal stream of perceived classifications and determine the best candidate class in order to disable the airbag in case of a child or an infant seat.

(a) (b) (c) (d)

Figure 2: Examples of each of the classes: (a) infant, (b) child, (c) adult, and (d) empty seat.

One unique condition that is experienced by this system is that there are times when the occupant's behavior can dramatically change the perceived class of the occupant. For example if an adult occupant reaches down to tie their shoe they can appear like an infant seat (see Figure 3), and a child that stands in the seat can appear to be an adult. We then need to be able to change the system beliefs as the evidence is gathered based on this changing world view.

(a) (b)

Figure 3: Demonstration of need for temporal evidential combining: (a) adult seated normally and (b) adult leaning forward and appearing to system to be an infant seat.

Figure 4 and Figure 5 provide a series of frames across the entire image sequence for a 5th percentile male passenger and a 5th percentile female passenger where they are moving and performing a number of hand and arm gestures to intentionally try to fool the system. These video sequences are ideal for demonstrating the real-world issues regarding integration of temporal streams of evidence, and clearly shows the roles temporal-based Kalman-filter can play.

Figure 4: Every 65 frames from sequence 1.

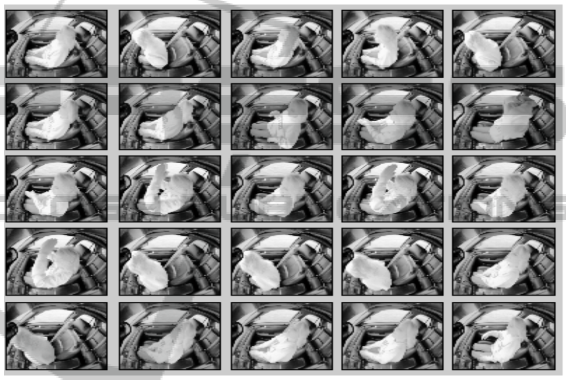

Figure 5: Every 25 frames from sequence 2.

5 PROPOSED STRUCTURE FOR A KALMAN FILTER FOR EVIDENCE FILTERING

Consider the estimate of a basic evidential state at some time increment k, to be $\hat{x}_E(k)$ and an incoming measure of such a state to be $x_{obs}(k)$. Assume an initial estimate of the uncertainty in that state is defined to be: σ_E^2 and the known uncertainty in the measurements to be σ_M^2. For simplicity we will also assume the state transition matrix and the measurement matrix are simply the identity matrix for the sake of clarity of the derivations.

The basic estimate update equation is (Gelb, 1974):

$$\hat{x}_E(k) = \hat{x}_E(k-1) + G(k) \cdot [x_{obs}(k) - \hat{x}_E(k-1)]. \tag{10}$$

After each update of the filter we compute a new estimate for the estimate uncertainty (Gelb, 1974):

$$\hat{\sigma}_E^2(k) = (1 - G(k)) \cdot \hat{\sigma}_E^2(k-1), \tag{11}$$

where the gain term is (Gelb, 1974):

$$G(k) = \frac{\hat{\sigma}_E^2(k)}{\hat{\sigma}_E^2(k) + \sigma_M^2(k)}. \tag{12}$$

Equations (10) through (12) represent the simplest form possible for the Kalman filter. In these equations, the value for σ_M^2 can be computed from either the signal-to-noise ratio of the sensor source, or in the case of a classifier such as for the above airbag application, it can be the overall probability of correct classification for the system or it can capture the local decision surface for a particular classification result. Note however, that the gain term defined in Equation (12) does not include the desired System Covariance which captures the uncertainty in the system model. To add this term we need to note that if there is an added system error h introduced at time k, and then the state for that time would actually be:

$$x_E(k) = x_E(k-1) + h(k). \tag{13}$$

This would then result in the covariance for the state estimate to be:

$$\hat{\sigma}_E^2(k) = \hat{\sigma}_E^2(k) + \sigma_h^2(k). \tag{14}$$

There are two key questions we must address: (i) what behavior do we want from an evidential filtering viewpoint as $\sigma_h^2(k)$ varies, and (ii) what does the term $\sigma_h^2(k)$ correspond to in the evidential reasoning domain.

To address these questions we will begin with this interesting point by Schubert, who mentions that "A high degree of conflict is seen if there is a representation error in the frame of discernment; while a small conflict may be the result of measuring error" (Schubert, 2008). Recall the conflict between two sources of evidence is defined to be (Shafer, 1976); (Schubert, 2008):

$$\mathrm{K}_{12} = \sum_{X \cap Y = \phi} m_1(X).m_2(Y), \tag{15}$$

If we substitute a term based on this conflict into Equation (15) we get:

$$\hat{\sigma}_E^2(k) = \hat{\sigma}_E^2(k) + \alpha_{rec} \cdot (1 - K_{12}(k)) \tag{16}$$

where α_{rec} is the recency factor which will serve to bias the resultant state estimate towards either recency or primacy. The resultant behavior of using the conflict in this manner will be that evidence will not be discarded or reassigned as in Dempster's rule, but rather will be added to the system at a reduced level. As this conflicting evidence continues to come into the system (assuming it is a sustained change in environment), it will become less and less conflicting as the masses evolve, and the gain will continue to increase as the belief system evolves from this evidence.

6 CONCLUSIONS AND FUTURE WORK

Figure 6 provides a graphical view of the incoming classification results from the sequence shown in Figure 4.

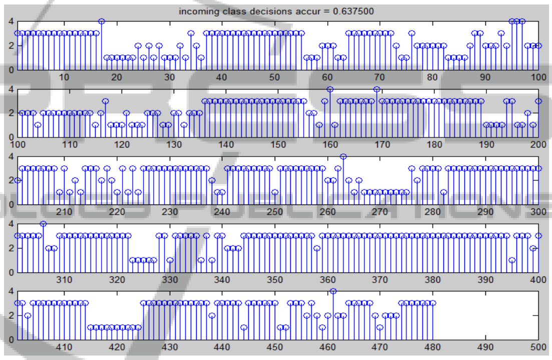

Figure 6: Incoming classifications (adult- class 3 is the correct class).

The classification result for the adult 50% male sequence (Figure 4 and Figure 6) is roughly 64% correct as is shown in Table 1. Note the Dempster-Shafer approach provides an improvement to roughly 76%. The four different entries for the Kalman filter are based on the relative nominal gain of the filter which depends on the recency factor defined in Equation (16). The high gain filter performance is quite poor due to the fact that with a higher gain, the filter is more heavily weighting the most recent classifier results. The ultra-low gain filter provides superior performance and more closely mimics human reasoning where: 'as information accumulates, beliefs are expected to become less sensitive to the impact of new information because this represents an increasingly small proportion of evidence already processed" (Hogarth and Einhorn, 1992). The improved performance of lower recency factors can most readily be seen in Figure 7 where the peak in classifier performance occurs for a recency factor of roughly 0.005.

One other parameter that must be initialized is the estimation uncertainty: σ_E^2. Figure 8 shows that fortunately, the performance of the system is not particularly sensitive to this value, however, a value below 0.1 provides the optimal classification performance.

Table 1: Classification Results for Adult Male Sequence.

Method	Correct Classification
Raw Data	.6375
Discounted Dempster-Shafer	.7667
Kalman (High Gain)	.6778
Kalman (Medium Gain)	.7001
Kalman (Low Gain)	.8096
Kalman (Ultra-low Gain)	.9142

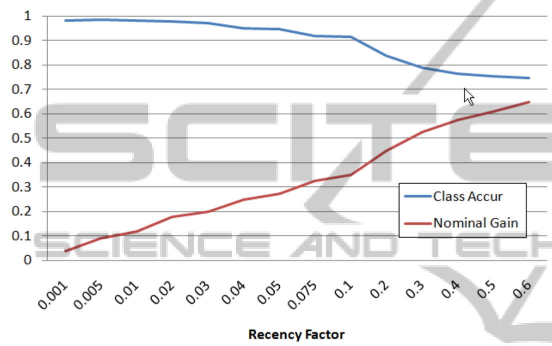

Figure 7: Classification results versus recency factor.

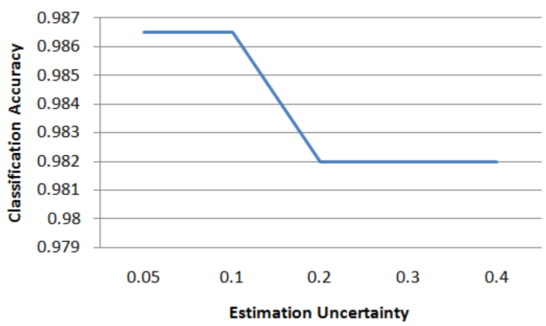

Figure 8: Classification results versus initial estimation uncertainty.

Figure 9 provides the incoming classifications for the sequence in Figure 5 where the initial classification was roughly 73% correct. The results for the 5th percentile female were also very encouraging for the Kalman filter-based approach, as can be seen in Table 2. Once again the ultra-low gain Kalman outperformed the discounted Dempster-Shafer algorithm. Thus for both datasets the ultra-low gain Kalman filter which heavily weights primacy of data similar to human reasoning outperformed the Dempster-Shafer approach.

While a very low gain filter is optimal for limiting change, we must analyze whether this bias against change can limit performance when change is required. To test this case, we started the data integration system at a point in the classification sequence where there was an extended period of false classifications, as can be seen in Figure 10, where the adult male occupant was leaning forward and appeared as an infant seat.

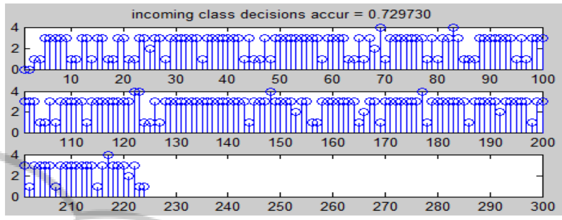

Figure 9: Raw incoming classifications for sequence 2.

Table 2: Classification Results for Female Sequence.

Method	Correct Classification
Raw Data	.7297
Discounted Dempster-Shafer	.9369
Kalman (High Gain)	.7477
Kalman (Medium Gain)	.8063
Kalman (Low Gain)	.9820
Kalman (Ultra-low Gain)	.9820

The raw incoming classification result for the data set that begins on an extended epoch of mis-classifications is roughly 63%. .

Table 3 provides the results for the Dempster-Shafer approach compared to the various Kalman filters of varying gain. Even in this dataset, the Kalman filter achieved 86% classification accuracy versus the Dempster-Shafer's 75%.

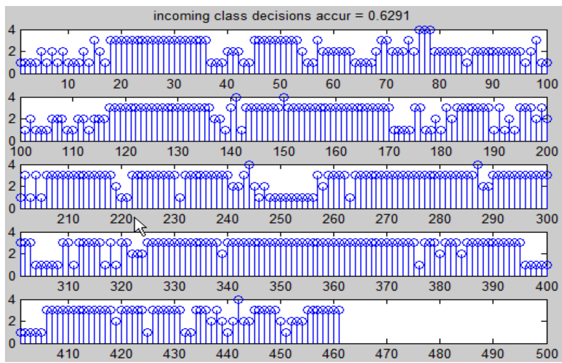

Figure 10: Incoming classifications (adult- class 3 is the correct class) with starting at epoch where classification begins incorrectly.

Table 3: Classification Results for Adult Male Sequence Starting at Epoch with Extended Wrong Classification.

Method	Correct Classification
Raw Data	.6291
Discounted Dempster-Shafer	.7549
Kalman (High Gain)	.6725
Kalman (Medium Gain)	.6920
Kalman (Low Gain)	.7961
Kalman (Ultra-low Gain)	.8568

In summary, the proposed Kalman filter-based temporal evidence accumulation algorithm outperformed the traditional Dempster-Shafer algorithm on all three of the datasets in this real-world application from an automotive airbag suppression system.

7 CONCLUSIONS AND FUTURE WORK

We have introduced the notion that when integrating evidence from a temporal stream of sensor inputs, an approach based on estimation theory and human reasoning provides superior performance to a traditional evidential reasoning approach based on Dempster-Shafer. We posited that this is due to the fact that the Dempster-Shafer approach is based on the concept of evidential independence which mandates the data be derived from different sensors (as originally envisioned by Dempster) and that for a single sensor a weaker statistical independence is all that can be assured.

We reviewed various approaches for evidence accumulation. We then developed an alternative Kalman filter representation from first principles and identified the key uncertainty terms as being: the estimate uncertainty: $\hat{\sigma}_E^2(k)$, the measurement uncertainty: σ_M^2, and the system uncertainty: $\sigma_h^2(k)$.

We proposed that the concept of conflict in the incoming evidential states can be used as a means of estimating the system uncertainty. The approach was tested on a real-world automotive airbag suppression application which consisted of a high resolution camera providing real-time classification inputs to our evidence accumulation system. An ultra-low gain Kalman filter out-performed the traditional Dempster-Shafer algorithm, which parallels the findings from human cognition where long term accumulation of evidence is best considered an estimation technique and recent evidence is highly discounted in favour of the historical accumulation of evidence.

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