Human Cognitive Models for Heritage Site Monitoring

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Abstract. Integrating evidence from a single sensor over time is becoming more common due to the Internet of Things (IoT). It can play a critical role in Heritage site monitoring, as networks of sensors are required to catalog and analyze data over extended periods of time. Researchers have often adopted the mechanisms used for multi-source integration, such as Bayesian conditioning and Dempster-Shafer reasoning. Research in human cognitive models provides an interesting alternative insights for accumulating evidence over time. We used this research as a foundation for the current approach which integrates the set theoretic nature of Dempster-Shafer theory with an estimation structure based on Kalman filtering. It is well suited for applications to Wide-area Sensor Networks (WSN) that are commonly found in heritage sites.

Keywords: Evidential Reasoning, Dempster-Shafer, Kalman Filter.

1 Introduction

"Cultural heritage management agencies are generally mandated with the responsibility of managing and protecting a finite archaeological resource base for a relevant region, state or nation… using various combinations of techniques, including excavation, site discovery and recording programmes, and … the application of predictive modelling" (Canning, 2005). The integration of data regarding these sites over time is a key element of predictive modelling. This data can take various forms including ground water contaminants, micro-seismic activity for site stability monitoring, air quality measures, etc. This data is then used to establish beliefs in the state of the sites. Evidential reasoning and belief updating has been a heavily researched area of AI for many years, with the most common approaches being based on Bayes or Dempster-Shafer probability theories.

A completely parallel effort in researching belief updating methods employed by humans (namely 'thinking humanly'), particularly methods related to updating beliefs over time, has primarily been a focus of the field of cognitive psychology (Russell & Norvig, 2021)(Farmer, 2017). Approaches based on human cognition have some interesting differences from those approaches from traditional AI, including: (i) humans are sensitive to the order of the incoming evidence, (ii) humans can reduce the impact of evidence over long evidence streams, (iii) humans tend to integrate evidence in an means that resembles estimation more than evaluation in standard AI models, and (iv) humans have the ability to forget evidence and change their mind towards a previously opposing belief (Baratgin & Politzer, 2007)(Farmer, M.E. 2017) (Wang, Zhang, & Johnson, 1999). Interestingly, the personalist view of Bayesian reasoning presumes that any individual that does not follow Bayes rule of conditioning for evidence accumulation is 'irrational' or 'inconsistent' (Shafer, 1976). It is much more likely that, rather than numerous human subjects in various psychology studies are behaving irrationally, but rather that the Bayes framework and other related evidence accumulation methods are inadequate when applied to sequential evidence accumulation (Wang P. , 2004).

In this paper we discuss an approach to evidence accumulation that is motivated by a common human cognitive model for belief updating. We extend that model by integrating the concept of ignorance that allows us to integrate information at various levels of abstraction. We also provides a convenient mechanism for forgetting evidence when dynamic environments call for it. As Josang, Costa, and Blasch observed: "Because different situations can involve different forms of belief fusion, there is no single formal model that is suitable for analyzing every situation (Jøsang, Costa, & Blasch, 2013)."

2 Exposition of the Investigation

Heritage sites require a variety of sensing modalities to protect them from a variety of natural and manmade threats. An overview of these sensing needs will be addressed in the following subsection. Discussions on mechanisms for integrating (i.e. fusing) this information over time will then be addressed in subsequent subsections.

2.1 Heritage Site Monitoring

"Monitoring is the act of **measuring change** in the state, number, or presence of characteristics of something (Walton, 2003)." Monitoring requires the repeated collection of a specific set or sets of data over time and then analyzing that data to detect the changes that are occurring. "Subsurface archaeological remains, earthworks, built structures, and landscape features are all susceptible to damage and change (Walton, 2003)." Figure 1 provides an overview of a typical heritage site management process. The elements of the process that can be supported by the human-based evidence accumulation framework presented in this paper are the stages of '*Undertake any simple steps to fill data gaps in data*' and '*Use data to compile assessment*'. Our integration of the concepts of ignorance and forgetting can also play a key role in dealing with missing data.

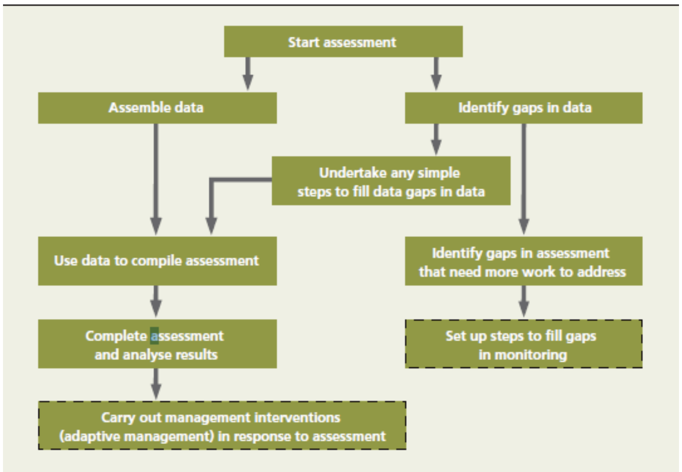


Fig. 1. Overview of Heritage Site Management Process (Hockings, et al., 2008)

The data used for the management of heritage sites is quite varied depending on the environment within which the site is situated. For example, masonry and stone structures rare key parts of our architectural heritage and these structures are particularly susceptible to "physical, chemical and biological processes which degrade their material and structural integrity, potentially leading to catastrophic failure (Hestera, Prabhua, Atamturktura, & Sorbera, 2017)."

Architectural structures are also susceptible to damage from vibrations. These can be macro-level seismic events such as those that occur in seismically active regions of the earth, and they can also be from micro-level seismic disturbances which are common in urban settings. "In contemporary urban areas vibrational waves are transmitted through air, producing noise, and through the ground to building foundations and from foundations to the upper floors. The majority of vibration sources are related to road traffic, metro systems and trains but construction activities, like pile driving and excavation by mechanical tools or blasting are important vibration sources as well (del Grosso & Basso, 2014)." Wave generation and propagation is very complex and is hence difficult to categorize, however, categorization is important since, for example, "frequent transit of heavy vehicles and construction works may induce vibrations largely exceeding the intensity of those caused by normal traffic and therefore may be responsible for damages [in heritage sites] beyond cosmetic (del Grosso & Basso, 2014)." In-situ vibration measurements to detect these types of activity can provide insight into the overall state of the structure. Typically, data is collected by placing sensors at various locations within the structure and the data can be used to estimate damage characteristic (Hestera, Prabhua, Atamturktura, & Sorbera, 2017).

"Monitoring microclimatic conditions is important in preventing deterioration of artwork or structural architecture. Microclimatic monitoring is a useful tool for the protection of works of art in museums or archives, as well as for monitoring structures hosting cultural heritage, such as frescos (Mesas-Carrascosa, et al., 2016)." "Climate change-induced impacts on cultural heritage and resources typically include sea level rise; flooding; coastal erosion; changing air and sea temperatures; changing humidity;

extreme weather events such as hurricanes, storms, and droughts; weathering; and changing soil and sediment conditions (Fatorić & Seekamp, 2017)." There are a variety of sensors associated with measuring these parameters over time. "Recent progress in electronics, wireless communications and the production of small-sized sensors provide new opportunities to monitor and control homes, cities, crops, and the environment. Monitoring in higher frequencies (1 datum/min) is interesting because of the greater recording potential of valuable information which leads to greater accuracy for statistical analysis (Mesas-Carrascosa, et al., 2016)."

Acidification of groundwater can have a significant impact on the erosion of archeological artifacts, and these levels must be monitored so that damaging levels can be predicted ahead of time if remediation/fortification of the sites is possible. It is important to note that more than half of the current world's population now lives in urban areas. The resulting concentration of human activities generates a wide range of impacts on the urban environment, other than the vibration issue mentioned earlier, and include effects such as contamination (Vrba & Adams, 2008). As many heritage sites are within urban settings, this contamination of groundwater can be a significant threat to many archeological sites. Additionally, "polluted runoff water from roads, soil and groundwater acidification by transport emissions and spills of various substances due to road and railway accidents can all have a serious influence on groundwater quality (Vrba & Adams, 2008)."

These urban settings also result in significant acid atmospheric emissions (sulphur dioxide-SO2, nitrogen oxides-NOX) which can be transported hundreds of miles over entire continents. The resulting chemically converted products (sulphuric and nitric acids) are major sources of regional pollution of soil and surface water (Vrba & Adams, 2008)." These sources of contamination can be particularly destructive to heritage sites and monitoring them over extended time periods is essential.

For groundwater in particular, but also for airborne contaminants, "an early warning monitoring strategy on a regional scale is an important part of the protection policy and management of public groundwater supplies (Vrba & Adams, 2008)." For groundwater monitoring, point monitoring, line monitoring and volume monitoring techniques are all employed. Point and line monitoring use networks of sensors that capture data both spatially and temporally. For volume sensors temporal analysis of the data stream is critical since trend analysis is performed. The use of networks of sensors is a common approach to site monitoring irrespective of the type of data being collected. A key issue in Wide-area Sensor Networks (WSNs) is how various applications such as event detection, signal tracking, and decision making can use the sensor measurements with increased confidence and as minimum energy consumption as possible in the presence of imprecise sensor readings (Izadi, Abawajy, Ghanavati, & Herawan, 2015). The integration of beliefs from these imprecise sensors over time is the task of the human cognition-based approaches discussed in this paper.

2.2 Evidential Reasoning for Sensor Network

Figure 2 provides an overview of the combined temporal and spatial processing in a sensor networks. The traditional sensor fusion across multiple sensors is shown vertically on the left, while the temporal fusion within an individual sensor is shown horizontally across the figure. Traditional methods such as Bayes conditioning and Dempster-Shafer have been shown to be quite effective for the vertical multi-sensor fusion across sensors. Limitations in these methods arise for the temporal integration within an individual sensor, however, and the current human-cognitive model approach provides a more appropriate model.

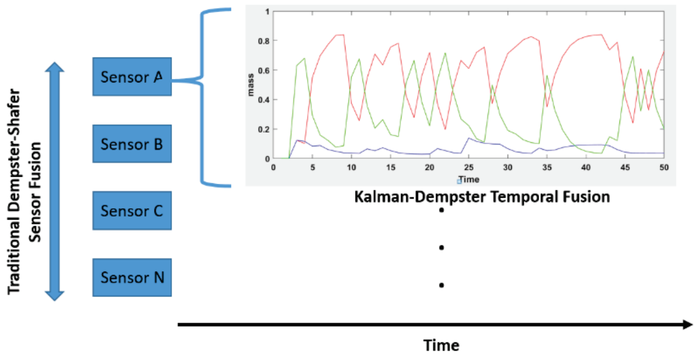


Fig. 2. Overview of traditional fusion across sensors versus temporal fusion over a single sensor.

Figure 3 provides an overview of the relationships between the various terms that have been adopted in the research space commonly referred to as fusion. The approach advocated here falls into the Sensor Fusion sub-space. Specifically, the method here is applicable to fusion of information over time from a single source. The subsequent integration across sensors is not a topic of discussion in this paper, however, the outputs from the temporal integration of single sensors does fit nicely into the traditional cross-sensor fusion frameworks.

The fusion mechanisms for heritage site monitoring must be able to integrate data of varying quality since "WSNs are intended to be deployed in environments where sensors can be exposed to conditions that might interfere with their measurements … sensors' measurements may be imprecise (or even useless) in such scenarios (Nakamura, Loureiro, & Frery, 2007)." One additional issue that arises with networks for which most classification systems handle poorly is missing data. Missing data can be caused by "poor network connectivity, faulty sensor systems, environmental factors and synchronization issues are the various reasons for the incomplete results (Krishnamurthi, Kumar, Gopinathan, Nayyar, & Qureshi, 2020)." While much research has been focused on missing data reconstruction, the method proposed here will utilize the concepts of ignorance and forgetting to handle missing data in sensor data streams.

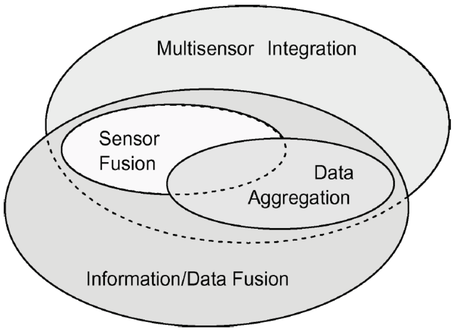


Fig. 3. Taxonomy of Fusion Terminology (Nakamura, Loureiro, & Frery, 2007).

Data streams from embedded sensors can represent a range of abstractions including raw sensor data, classification probabilities or beliefs, and discrete event notifications. These outputs are then fused differently based on their modality. For this research we focus on the classification outputs from processing raw signal data. For example, if water monitoring sensors are used they could output organic or inorganic contaminants, and these can be further broken down based on the type of sensors into categories such as hydrocarbons, phosphates, etc. For discrete outputs such as classifications and event detection, they would have some level of confidence associated with them. These can be formulated into two methodologies, one based on integrating probability mass assignments and the other based on integrating beliefs.

The approaches from probability mass assignments begin with Bayes' conditioning for a hypothesis A given new evidence, E, where E is 'known' to be true (Shafer, 1976):

$$p_2(A) = p_1(A \mid E) \tag{1}$$

Dempster-Shafer theory provides an alternative to conditioning through their rule for combining basic probability mass assignments (Shafer, 1976):

$$m_1 \oplus m_2(Z) = \frac{\sum_{X \cap Y = Z} m_1(X).m_2(Y)}{1 - \sum_{X \cap Y = \phi} m_1(X).m_2(Y)} \tag{2}$$

where *X*, *Y* and *Z* are the elements of the power set $P(\Theta)$ of all the hypothesis options. Based on the updated masses Dempster then computes the belief in hypothesis A according to (Shafer, 1976):

$$Bel(A) = \sum_{Y \mid Y \subseteq A} m(Y) \tag{3}$$

Note in the mass assignment methods there are some key limitations for application to temporal fusion, i) there is no order dependence which means the time series could have appeared in any order which is inappropriate when monitoring environments and looking for change, and ii) there is no way to discount the incoming information based on its quality, and iii) the entire past history is considered with the same weight as the most recent sample. These are all limitations we will show that can be removed by adopting a human-cognitive model-based approach.

The models based on working directly in belief space rather than probability mass space was pioneered by Premaratne, et al. using: (Premaratne, Dewasurendra, & Bauer, 2007):

$$Bel_{k+1}(B_1) = \alpha_k \cdot Bel_k(B_1) + \beta_k \cdot Bel_k(B_1 \mid A) \tag{4}$$

where the weights are constrained by $\alpha_k + \beta_k = 1$ and they propose α_k to be:

$$\alpha_k = 0.5\left[1 + \sqrt{(n-1)/w}\right] \tag{5}$$

where n is the number of times a pieces of evidence has been detected and w is the number of time windows where detection was possible. Premaratne, et al note: "…when encountered with the same streaming information continuously, the belief converges to a value decided solely by this incoming information" (Premaratne, Dewasurendra, & Bauer, 2007). The weight selection provides support for primacy and recency by controlling the relative importance of new versus historical evidence.

Dewasurendra, et al extend this work to integrate beliefs based on their frequency of occurrence, using (Dewasurendra, Bauer, & Premaratne, 2007):

$$Bel_k(B) = \sum_{i=1}^{N} \alpha_i \cdot Bel_{k-1}(B) + \sum_{i=1}^{N} \beta_i \cdot Bel_{k-i}(B \mid A) \tag{6}$$

and

$$\sum_{i=1}^{N} \alpha_i + \sum_{i=1}^{N} \beta_i = 1 \tag{7}$$

The α and β are weights which are defined to produce a desired transfer function for detecting the frequency behavior of the evidence being analyzed. Notice in both of these cases the evidence is weighted by its frequency of occurrence rather than any quality measure of the information.

2.3 Belief Revision in Human Psychology

Cognitive research has proposed numerous models for human's integration of beliefs over time (Farmer, 2011) with the work by Hogarth and Einhorn (Hogarth & Einhorn, 1992) being the definitive model. Human cognitive research shows we tend to work in a belief space and not a probability space (Hogarth & Einhorn, 1992) (Baratgin &

Politzer, 2007). They address evidence accumulation through a model employing anchoring and subsequent adjustment to these beliefs (Hogarth & Einhorn, 1992):

$$S_k = S_{k-1} + w_k\left[s\left(x_k\right) - R\right], \tag{8}$$

where

$$w_k = \begin{Bmatrix} \alpha S_{k-1} & \text{for } s\left(x_k\right) \le R \\ \beta\left(1 - S_{k-1}\right) & \text{for } s\left(x_k\right) > R \end{Bmatrix}, \tag{9}$$

and 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. These weights provide sensitivity towards integrating evidence, with different weights being employed for evidence considered negative or positive when compared to the anchoring level of support R. The impact of a long sequence of evidence can also be reduced through these weights. Hogarth and Einhorn note "as information accumulates and as people become more firmly committed to their beliefs, values of α and β [set internally by the person] would decline in a long series of evidence items" (Hogarth & Einhorn, 1992). Note the structure of the equation for S_k is structured as in an estimation format rather than an evaluative format like the Bayesian conditioning. There has previously been some interest in the ideas of estimation for beliefs, but it had not previously been tied to foundations in human cognition (Cossart & Tessier, 1999). A common formulation for estimation is the Kalman filter (Gelb, 1974). While applied to numerous sensor data applications it had not been widely applied to beliefs (Wu, Siegel, & Ablay, 2003).

2.4 Integration of Dempster-Shafer with Kalman Filters for Sensor Fusion

The traditional Kalman filter estimation equation is (Gelb, 1974):

$$x_{est}\left(k\right) = x_{pred}\left(k \mid k-1\right) + G\left(k\right) \cdot \left[z\left(k\right) - H\left(k\right) x_{pred}\left(k \mid k-1\right)\right] \tag{10}$$

where $x_{est}\left(k\right)$ is the estimated state vector for the system at time , z(k)are the measurements, H(k) is the measurement matrix that converts measurements to the state vector parameters, and $x_{pred}\left(k \mid k-1\right)$ is the prediction of the state vector to the current time, k, and G(k) is the gain matrix. Sensors produce measurements in probability mass space (e.g. the outputs of a classification algorithm to estimate the probability of a water sample having various levels of acidity), however, to mimic the human cognitive model, we will convert these probability measures using Dempster's definition of beliefs, Equation (3). The basic Kalman estimation equation is then modified in the following manner, where note the Measurement matrix H(k) is applied to the incoming measurements rather than to the state vector (Farmer, M.E. 2017):

$$x_{est}(k) = x_{pred}(k \mid k-1) + G'(k) \cdot \left[H_{Bel}^{T}(k) z(k) - x_{pred}(k \mid k-1) \right] \quad (11)$$

Interestingly, this equation can be rewritten into the form (Farmer, M.E. 2017):

$$x_{est}(k) = \left(1 - G(k)\right) \cdot x_{pred}(k) + G(k) H_{Bel}^{T}(k) x_{obs}(k) \quad (12)$$

which is identical in structure to Equation (8) from the Hogarth and Einhorn model for human sequential evidence accumulation.

The basic formulism for the Kalman filter has two tasks, prediction and the estimation, with the estimation task defined by Equation (11). The prediction equation for the state vector is thus defined as (Gelb, 1974):

$$x_{pred}(k+1 \mid k) = \Phi(k) x_{est}(k) \quad (13)$$

where $x_{est}(k)$ is the estimated state vector for the system at time k using all the information available up to time instance k, and $\Phi(k)$ is the state transition matrix which describes the dynamics of the system as it moves from time k to the next time instance k+1. For traditional physical systems the transition matrix $\Phi(k)$ captures the Newtonian mechanics of the system. For evidence estimation, however, there are options for its form. If we want beliefs to be static over time even if there is no new measurement input (i.e. the beliefs dead-reckon, or glide along at the same values) then the state transition matrix is simply the identity matrix. In dynamic environments, however, lack of new evidence may need to lead to increased ignorance, which means the current beliefs need to be slowly forgotten (Ricker, Spiegel, & Cowan, 2014). This is a common tendency in human cognition, for example, if it is partly sunny when we enter work, but don't see the sky all day then we will not be certain the sky is still partly sunny at the end of the day. We will address this concept of forgetting later in the paper.

The measurements z(k) are based on the probability mass assignments provided by the sensor. Salzenstein and Boudraa note: "An information source assigns mass values only to those hypotheses for which it has direct evidence" leading to a measurement vector (Salzenstein & Boudraa, 2004):

$$z(k) = \begin{Bmatrix} m(\{A(k)\}) \\ m(\{B(k)\}) \\ m(\{C(k)\}) \end{Bmatrix} \quad (14)$$

However, just using the atomic masses often does not reflect the true confidence in the measurements because no training set for a classifier completely captures the intricacies of the actual problem. Le Hegarat-Mascle, el al then note: "in most cases, no other compound hypothesis, but Θ is considered [where Θ is the set representing complete ignorance.]" (Le Hagarat-Mascle, Bloch, & Vidal-Madja, 1997). In this case the measurement vector would take the form:

$$z(k)=\left\{\begin{matrix} m(\{A(k)\}) \\ m(\{B(k)\}) \\ m(\{C(k)\}) \\ m(\{A(k),B(k),C(k)\}) \end{matrix}\right\} \tag{15}$$

where the last term, m({A,B,C}) is mass in the set of complete ignorance. The beliefs state vectors $x_{est}(k)$ and $x_{pred}(k|k-1)$ hold the complete Dempster-Shafer belief space, which for three possible hypotheses, A, B, and C, would be the terms: {Bel(A), Bel(B), Bel(C), Bel(A,B), Bel(A,C), Bel(B,C), Bel(A,B,C)}. Note the set structure allows us to represent information at varying degrees of abstraction, again another common mechanism in human cognition, rather than managing all our information at the atomic level as is done in Bayesian conditioning (Wolf & Knauff, 2008) (Nie, Müller, & Conci, 2017). In state vector form, this takes the form (Farmer, M.E. 2017).

$$x_{est}(k)=\left\{\begin{matrix} Bel(\{A(k|k)\}) \\ Bel(\{B(k|k)\}) \\ Bel(\{C(k|k)\}) \\ Bel(\{A(k|k),B(k|k)\}) \\ Bel(\{A(k|k),C(k|k)\}) \\ Bel(\{B(k|k),C(k|k)\}) \\ Bel(\{A(k|k),B(k|k),C(k|k)\}) \end{matrix}\right\} \tag{16}$$

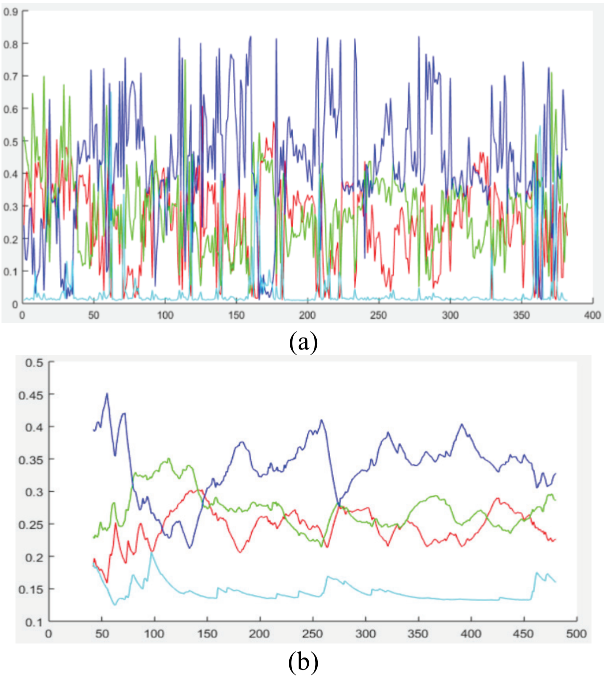
Dempster's definition of beliefs is incorporated into the measurement matrix as follows (Farmer, M.E. 2017):

$$H_{Bel}(k)=\left\{\begin{matrix} 1 & 0 & 0 & 1 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{matrix}\right\} \tag{17}$$

Figure 4 provides typical results from a four-class classification problem. While this data is from another application, it could easily be seismic event classifications, labeled: light/normal traffic, heavy vehicle, light/moderate natural seismic, and strong/severe seismic and the vibration sensor is measuring accelerations over time and classifying the signal stream into these classes. The Dempster-Shafer set concept's importance can be seen at times 150 and roughly 275, where the beliefs in three of the four classes are nearly equal. In these areas the true beliefs are best captured by belief in the set {A,B,C} rather than beliefs in the individual sets. Notice also that the inputs are quite noisy which is one key benefit of this human-cognitive mode approach, in that it allows for very inexpensive, lower fidelity sensors and classifiers to be integrated over time to provide much higher fidelity results which is an important consideration for WSN systems that may be integrated into heritage sites for monitoring.

Recall, one interesting aspect of human cognition is forgetting (Ricker, Spiegel, & Cowan, 2014). To accommodate forgetting, the state transition matrix takes on the form in Equation (18) where α is the preservation rate for the beliefs (Farmer M. E., 2019). Note that forgetting is accomplished by flowing beliefs to higher cardinality belief sets. This is motivated from the observation that the highest cardinality evidence set is the set of complete ignorance in Dempster-Shafer. Thus, eventually the system will devolve into one with no fixed beliefs and only being committed to complete ignorance.

$$\Phi = \left\{ \begin{array}{ccccccc} \alpha & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \alpha & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \alpha & 0 & 0 & 0 & 0 \\ 1-\alpha & 1-\alpha & 0 & \alpha & 0 & 0 & 0 \\ 1-\alpha & 0 & 1-\alpha & 0 & \alpha & 0 & 0 \\ 0 & 1-\alpha & 1-\alpha & 0 & 0 & \alpha & 0 \\ 0 & 0 & 0 & 1-\alpha & 1-\alpha & 1-\alpha & 1/\alpha \end{array} \right\} \tag{18}$$



(a)

(b)

Fig. 4. Typical input and output atomic beliefs, (a) input belief stream, and (b) estimated output stream (Farmer, M.E. 2017).

Figure 5 shows how an initial set of evidence flows into higher cardinality sets and ultimately into the set of complete ignorance. The rate of decay of beliefs can be tailored for the specific application by the preservation rate. As the belief in complete ignorance grows the belief in the set {1, 2, 3, 4} which grows.

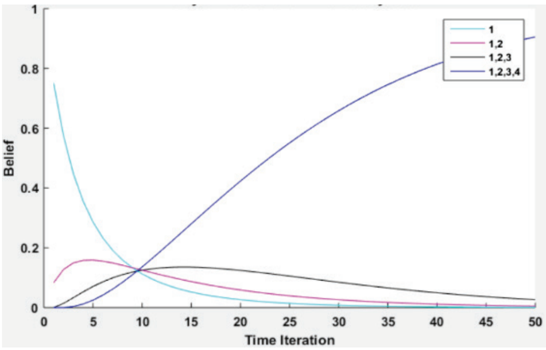


Fig. 5. Behavior of belief forgetting over time using preservation rate $\alpha = 0.9$ (Farmer M. E., 2019).

3 Conclusions

Heritage site monitoring is required for protecting these cultural sites from a variety of threats, both manmade and natural. Wide-area Sensor Networks (WSN) have been shown to be effective for monitoring wide varieties of data. Processing of this information can be facilitated with a model for evidence accumulation based on human cognitive models that integrate concepts from Dempster-Shafer probability theory and Kalman filter estimation theory. The resulting approach has numerous interesting characteristics and abilities such as the ability to integrate information at varying levels of abstraction, to intelligently integrate long temporal streams of information, and to even forget when periods of ignorance due to sensor drop-outs and other effects occur.

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