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Trustworthiness Modelling on Continuous Environmental Measurement

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Abstract: In the domain of environmental sciences, measurement is the process that maps some observed phenomenon to a formal measurement value, the latter being the result of a measurement process. The measurement process relies on data representing physical quantities of possibly continuously changing phenomena. Because of the inherent imprecision of this source data and interpretations made within the measurement process itself, the measurement processes and their measurement values are plagued with quality issues. Many of these quality issues may be parameterised and provided as metadata of the measurement value, e.g. precision, resolution, trustworthiness. Of these, the trustworthiness quality parameter is evaluated by the consumer of the measurement value; this evaluation is a subjective perception of the level of momentary reliance justifiably placed on the measurement value and possible quality parameters. Initially the level of trustworthiness is thus vacuous with the consumer's trustworthiness building up by gained evidence in the provider in providing this type of a measurement value. In this paper we define a method for representing, calculating and monitoring the trustworthiness parameter placed on a provider providing measurement values. The inherent imprecision of any measurement value is considered as a level of (un)certainty with a three-valued representation. The presented method is based on Dempster-Shafer theory of evidence and uses Subjective Logic to calculate with the trustworthiness. We apply techniques of reputation based trustworthiness for a meaningful reliability analysis in environmental sciences. We validate our method on data from the indoor environment of a residential house.

***Keywords**: Trustworthiness; Uncertainty; Sensor data; Evidence*

1. INTRODUCTION

A contemporary problem when processing inherently uncertain data is assigning a confidence level on the output. Traditional means of dealing with this problem include statistics. Computationally heavy analysis of models by statistics assumes the environment as a static element motivating the statement that "all models are wrong, but some are useful" (Box and Draper, 1987). This statement holds equally true for environmental modelling. Firstly, the environment is inherently inconsistent, making any logical model of this a simplification of reality (Abrial 2010). This raises the practical question of the model's distance to reality indicating its usefulness (Box and Draper, 1987). Secondly, as the environment (nature) is informal, any measurement on it is inherently uncertain. Hence, all computerized (formal) tasks are triggered by an informal event, e.g. a key press, an observation. Moreover, all computer-aided information is eventually used on the informal environment, e.g. to adjust a valve and stigmergically affect the environment, to display information to the human and let the human decide further actions. Hence, it is fair to state that the beginning and the end of each task is informal (Zemanek 1980) motivating that the formal mode (computations) merely extends the informal mode; they do not replace it (Naur 1982). These motivations highlight the ongoing challenge of making sense of sensory data (Tollefson 2011; Balazinska et al. 2007) due to the inherent presence of uncertainty in any meaningful computer-aided task. The problem domain described above is common to all domains processing vast amounts of continuous data with ever varying uncertainty levels for providing an output. Clearly, environmental modelling is such a domain. Experience-based reputation systems (Jøsang et al. 2007) is another one.

In this paper we present a method from experience-based reputation systems applied to the environmental modelling domain. The method relies on Subjective Logic (Jøsang et al. 1997, 2014), hereafter denoted SL, that is related to the Dempster-Shafer theory of evidence and it may be used to analyze Bayesian networks (Jøsang et al. 2006a). The proposed method addresses many challenges of environmental measurement, including those where the deviating quality of sensory observations is evident. Hence, this method is the contribution of this paper. The observation and process uncertainty are treated in the three-valued representation of SL featuring an extensive set of rules, including sequential and parallel composition of values. It is therefore very well suited for contemporary service oriented visions such as the “ModelWeb” (Bastin et al. 2013) or architectures alike the sentient object where one model may provide input to another (Biegel and Cahill 2004; Fitzpatrick et al. 2002; Coutaz and Rey 2002; Rey and Coutaz 2004; Gray and Salber 2001), depicted in Figure 1.

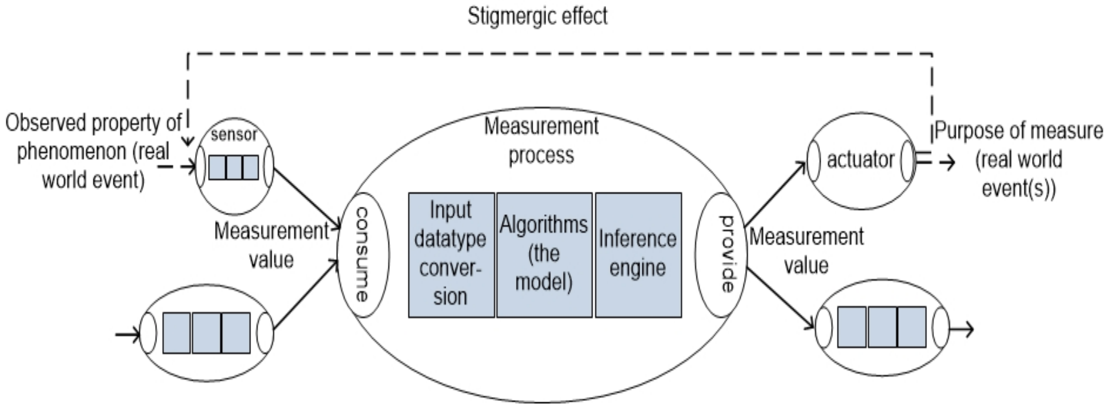

Figure 1: The Sentient Object model

This paper is organized as follows. Section 2 outlines the proposed method for deriving the trustworthiness of environmental measurement with a formal presentation of the foundations of experience-based trustworthiness and SL. Section 3 presents the result of this method when applied to an indoor environment of a residential house. Specifically, we present the result of calculating the indoor temperature of a residential house based on the weighted mean by trustworthiness of four temperature sensors and provide this result’s trustworthiness. Section 4 discusses shortly the findings and Section 5 concludes the paper.

2. TRUSTWORTHINESS OF A MEASUREMENT VALUE

A measurement value is the output of a measurement process that maps a nonempty subset of observed properties of phenomena or provided output(s) of other measurement process(es) into more meaningful data with respect to the purpose of the measurement. Needless to say, that output abstracts (incorporates) all uncertainties of the underlying data and inaccuracies of the models. On this, trustworthiness as a quality parameter (Buchholz et al., 2003) is identified and noted as a complex parameter (Buchholz et al. 2003; Wegdam et al. 2007). Trustworthiness is considered either policy-based or experience-based (Bonatti et al. 2005). Policy-based is used when Boolean reasoning is applied while experience-based is used when the level is based on a priori recorded events, i.e. evidence. Hence, experience-based trustworthiness fits the domain of environmental modelling better.

We define (experience-based) trustworthiness as a parameter between the consumer (trustor) and the provider (trustee) in line with McKnight and Chervaney (1996) with the difference that the trustee may be a matter of any kind:

Definition 1. Trustworthiness: “The extent to which a trustor is willing to depend on a trustee in a given proposition with a feeling of relative security, even though negative consequences are possible.”

Some notable issues in this definition are that trustworthiness is a feeling of unwarranted expectations on the trustee, that it is proposition specific, and that it is relevant only when something can go wrong. As either the expectations of the trustor or the performance of the trustee may change, the level of trustworthiness is subject to continuous variations and is always incomplete, i.e. complete trustworthiness is a mere theoretical concept. This motivates the use of a continuously varying parameter to model trustworthiness derived from distinct experiences. Hence, trustworthiness is not uniform and cannot be statistically modelled. The next sections present a mathematical framework for trustworthiness.

2.1 Theory for a Three-valued Parameter

The theory is based on Dempster-Shafer theory of evidence where the set of possible exclusive and exhaustive outcomes of any event is X. The powerset 2^X then denotes all combinations of outcomes, hereafter propositions. Let mass m denote the evidence in favour of a specific outcome with $m : 2^X \to [0,1]$, $m(\emptyset) = 0$ and $\sum_{A\in 2^X} m(A) = 1$. This additivity is modelled on a mass space, e.g. $X = \{x_1, x_2, x_3\}$ where the mass ‘x_1 or x_2’ denote the certainty of not x_3, but not certain whether x_1 or x_2, i.e. the mass of $(\{x_1, x_2\})$. In addition to the mass m, the belief bel defined on $A \subseteq X$ as $bel(A) = \sum_{B\subseteq A} m(B)$ denotes the ‘certainty’ or ‘evidence’ in favour for the propositions A; for singleton A $m = bel$. Plausibility pl denotes the maximal probability that the evidence gives rise to. We have that $pl \geq bel$ and $pl(A) = \sum_{A\cap B\neq\emptyset} m(B)$ and $pl > bel$ whenever $m(X) \neq 0$. Moreover, let the complement of bel be $\overline{bel}$ defined on $\bar{A} \subseteq X$ where $\bar{A} \cap A = \emptyset$ and $\bar{A} \cup A = X$, then the evidence against $bel(A)$ is $\overline{bel}(\bar{A})$, i.e. $pl(A) = 1 - \overline{bel}(\bar{A})$. The difference between$bel(A)$ and $pl(A)$ denotes the level of uncertainty, i.e. the level of lacking evidence in favour of or against a proposition. More elaborate explanations of these concepts in the context of trustworthiness may be found elsewhere (Neovius 2012; Neovius and Sere 2013).

2.2 Experiences, their Type, Decay and Abstraction

An experience Exp captures the level of satisfaction in a proposition the trustor first-handedly perceived on the data provided by the trustee at a given time. We represent such an *Exp* formally by a four-tuple $(\delta, \epsilon, \zeta, \eta)$ where $\delta = trustee$, ϵ is the datum (typically time), ζ is a proposition and $\eta \in score$. We write ϵ_{index} when we indicate all experiences prior to $index$ and only ϵ for an arbitraryvalue. An agent’s history is a set of such experiences, i.e. $Exp^{T_1} = \{(\delta, \epsilon, \zeta, \eta)\}$ where T_1 is the agent in question. To acquire a specific projection of the experiences, we write $Exp^{T_1}(sel_\phi)$ where sel_ϕ defines the projection, e.g. $Exp^{T_1}(T_2, \epsilon_p, temperature) = \{(\epsilon, \eta)\}$ where $\epsilon_i \leq \epsilon_p$ for $i = 0, 1, \ldots, p$, i.e. ϵ_p indicates the time for this snapshot and $Exp^{T_1}(T_2, \epsilon_i, temperature) = \eta$ a specific experience.

Our method defines the score of an experience as a tuple (α, β) where α denotes satisfaction, and β denotes dissatisfaction. For (α, β) it holds that $\alpha, \beta \in [0, 1]$ and $\alpha + \beta \leq 1$; much alike bel and $\overline{bel}$ in Section 2.1. The possible subadditive feature enables uncertainty to be expressed on an experience where score $\eta = (0, 0)$ is equal to no experience. Dually, absolute experiences are when scored either (1, 0) or (0, 1) and dogmatic when $\alpha + \beta = 1$. In addition, this type enables simple summation on the η-projection of any set of experiences with a given agent T_1 so that initially $\sum_{i=0}^{p} Exp^{T_1}(T_2, \epsilon_i, \zeta) = (0,0)$ indicates no evidence. Adding experiences observed at ϵ_p by T_1 is straightforward, $Exp^{T_1}(\epsilon_p) = Exp^{T_1}(\epsilon_{p-1}) \cup \{(\delta, \epsilon_p, \zeta, \eta)\}$ when $0 < p$.

Decay of an experience is motivated by that newer experiences should weigh more than older. Critical for decay is to recognise the independence of α and β, i.e. that decay must not subvert the experience, merely reduce its weight. Here, formal treatment of subadditivity in terms of uncertainty is fundamental. Let $0 \leq \lambda \leq 1$ be a decay factor (one of possibly many) on the experiences. Realistically, consider λ a factor on decay by time, i.e. $\lambda^{\epsilon_p - \epsilon}$. The decayed experiences at ϵ_j, identified by prefix d_{ϵ_j} are $d_{\epsilon_j}(Exp^{T_1}) = \{(\delta, \epsilon, \zeta, \lambda^{\epsilon_j - \epsilon} * \eta)\}$ and with projections, $d_{\epsilon_k}(Exp^{T_1}(T_2, \epsilon_k, \zeta)) = \{(\epsilon_i, \lambda^{\epsilon_k - \epsilon_i} * \eta)\}$

where $i \leq k$. Thus, the closer λ is to 1, the less 'forgetting' is imposed with $\lambda = 1$ indicating no decay (consistent setting) and $\lambda = 0$ full decay (stochastic setting). Abstraction Abs of experiences is the merger of the scores, formally denoted in function 1.

$$Abs_{\epsilon_k}\left(Exp^{T_1}(T_2, \epsilon_k, \zeta)\right) = \sum_{i=0}^{k} d_{\epsilon_k}\left(Exp^{T_1}(T_2, \epsilon_i, \zeta)\right) \quad (1)$$

Thus, abstraction provides a mathematical sound decayed pair $(\alpha^{Abs}, \beta^{Abs})$ that indicates the weight between satisfactory and unsatisfactory observations.

2.3 Subjective Logic

SL is probabilistic logic based on the Dempster-Shafer theory of evidence. SL expresses the level of trustworthiness on a frame of discernment, i.e. on a proposition among the exclusive and exhaustive frame of possible outcomes. Recall Section 2.1, let this frame be X with cardinality $c = |X|$ and $c \geq 2$. An opinion on this frame is a 3-tuple $(\vec{b}, u, \vec{a})$ of a belief mass vector, uncertainty mass scalar and base rate vector a in a c-nomial barycentric coordinate system. The vectors $\vec{b}$ and $\vec{a}$ are vector-valued functions on the propositions of $X = \{x_1, x_2, x_3\}$ with range $[0,1]^c$ and $\sum_{x_i \in X} \vec{b}(x_i) \leq 1$, e.g. $\left(\vec{b}(x_1), u, \vec{a}(x_1)\right), \left(\vec{b}(x_2), u, \vec{a}(x_2)\right), \left(\vec{b}(x_3), u, \vec{a}(x_3)\right)$ for $c = 3$. Coarsening this to a binomial opinion $c = 2$ is straightforward by partitioning X to $X = \{x, \bar{x}\}$ with a binomial opinion ω of $\vec{b}(x), u, \vec{a}(x)$ where disbelief is $\vec{b}(\bar{x}) = 1 - \vec{b}(x) - u$, or equivalently $\sum_{\bar{x} \in X} \vec{b}(\bar{x})$ and $\vec{b}(x) + \vec{b}(\bar{x}) + u = 1$. Based on such a binomial opinion the posterior expectation value $E(\omega)$ is defined as $E(\omega) = \vec{b}(x) + u * \vec{a}(x)$ denoting the most likely outcome given the evidence. The level of binomial trustworthiness can be illustrated by a triangle with vertices bel, $\overline{bel}$ and u, trinomial trustworthiness by a tetrahedron and an n-nomial in an n-dimensional barycentric coordinate system.

SL features a set of functions to calculate with distinct opinions. The most central include multiplication / comultiplication and consensus / discounting. The functions are found elsewhere (Jøsang and McAnally 2004; Jøsang 2001). For brevity, consider two disjoint frames $X = \{x, \bar{x}\}$ and $Y = \{y, \bar{y}\}$ by agent T_1 on T_2 then multiplication is $\{(x, y)\} \in X \times Y$ and comultiplication is $\{(x, y), (x, \bar{y}), (\bar{x}, y)\} \in X \times Y$, i.e. composing the frames by proposition. Discounting and consensus operate on one frame and one subject where discounting is when agent T_1 relies on T_2 to recommend another agent T_3 providing the experiences in case the trust of T_2 in T_3 is discounted by the trust of T_1 in T_2. Consensus is when T_1 has experiences of one proposition on several agents, e.g. T_1 has experiences of $x \in X$ regarding T_2 and T_3 recommending say T_4, then consensus consists in the merger of T_2 and T_3 experiences in T_4. Functions for discounting and consensus are found elsewhere (Jøsang et al. 2006b). If the opinions are dogmatic ($u = 0$), SL behaves as 'traditional' probabilities and if the opinions are absolute ($\vec{b}(x) \in \{0, 1\}$ and $u = 0$) SL behaves as Boolean logic.

A binomial opinion ω in SL is related to abstracted experiences score $(\alpha^{Abs}, \beta^{Abs})$ by the mapping function (2), originally proposed by Jøsang et al. (1997) and later elaborated by Jøsang et al. (2006a). In this mapping, W denotes the non-informative prior weight that when $W > 0$ assures a level of uncertainty, i.e. $u > 0$. Typically $W = 2$ as of binomiality and equal initial distribution in a beta probability density function (Bpdf). The relation with the experiences is thus evident and the $(\alpha^{Abs}, \beta^{Abs})$ may illustrate the trustworthiness as a Bpdf with inputs defined $(\alpha^{Abs} + W * a, \beta^{Abs} + W * (1 - a))$. Thus, with $W = 2$ and $a = 0.5$ the initial distribution is even, denoting that all propositions are equally possible; or denoting the situation of "do not know" as for full uncertainty.

$$\omega \begin{cases} b = \dfrac{\alpha^{Abs}}{\alpha^{Abs} + \beta^{Abs} + W} \\ d = \dfrac{\beta^{Abs}}{\alpha^{Abs} + \beta^{Abs} + W} \\ u = \dfrac{W}{\alpha^{Abs} + \beta^{Abs} + W} \\ a = base\ rate \end{cases} \Leftrightarrow \left.\begin{matrix} \alpha^{Abs} = \dfrac{Wb}{u} \\ \beta^{Abs} = \dfrac{Wd}{u} \\ a = base\ rate \end{matrix}\right\} tuple \quad (2)$$

3. CASE STUDY: INDOOR TEMPERATURE MEASUREMENT

As a proof of concept, we have applied the presented method of calculating a level of trustworthiness on an indoor dataset obtained from four disjoint measurement processes that provide time-stamped temperature values. The frequency of indoor measurement values is 10 seconds on a time span of one year, with a varying level of incompleteness. The frequency of outdoor measurement value is 1 day. The goal of the study is to acquire the most probable indoor temperature by calculating the weighted mean of the measurement values by their trustworthiness. Thus, the method recognises unreliable processes and weighs their values accordingly. Due to decay λ, transient errors are captured where the process can recover its level of trustworthiness. We have defined the experience (value) score evaluation by the three-sigma rule of standard deviation from the normal distribution of the posterior weighted mean. Hence, the level of deviation of each measurement value from the weighted mean defines its evaluation score. We discarded absent values and measurement values not in the interval $[-50°C, 50°C]$, e.g. the dataset contained a faulty (impossible) reading -49950°C that due to its level would have significantly affected the analysis.

From the trustworthiness perspective, as all indoor measurement values are of temperature, they all evaluate the same proposition. The exclusive and exhaustive scores denote the level of trustworthy and untrustworthy, respectively. Hence, the (α, β) notation qualifies where the levels are defined by the three-sigma deviation rule from the weighted mean. With one data point every 10 seconds and $\lambda = 0.95$ per second, an observation weighs ~60% of its original weight when recorded and 0.2% after 2 minutes enabling, thus, prompt reaction to errors. This is illustrated in Figure 2, where the primary vertical axis denotes the trustworthiness level, the secondary vertical axis denotes the temperature °C, and the horizontal axis denotes time as mm.dd.yyyy hh:min.

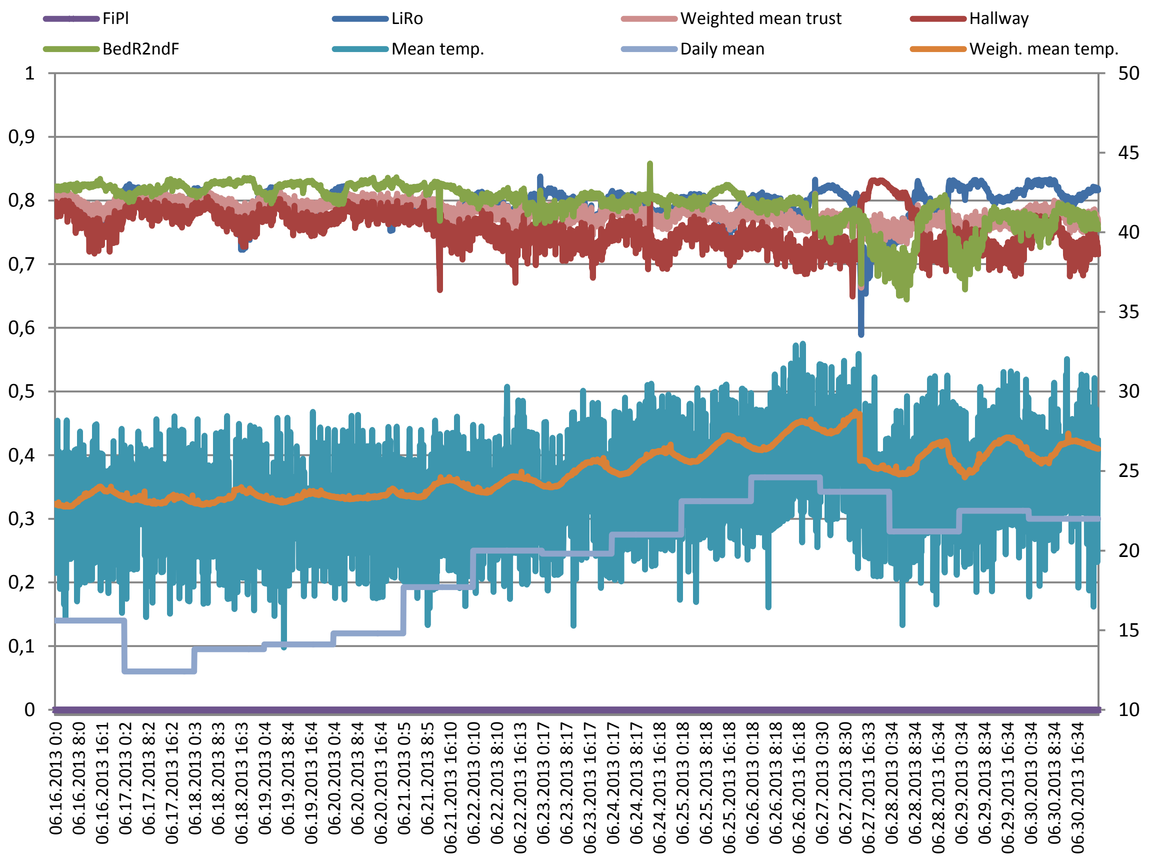

Figure 2. Indoor temperature and measurement processes' trustworthiness in June

The abbreviations in the legend of Figure 2 are as follows. On the left scale: FiPl = fireplace sensor, LiRo = living room sensor, Hallway = hallway sensor, BedR2ndF = bedroom 2nd floor sensor; and on the right scale: Mean temp. = mathematical mean temperature in °C, Daily mean = the daily mean temperature outdoor in °C and Weigh. mean temp. = the weighted mean temperature in °C. What the plot reveals is that, once the outdoor temperature (daily mean) exceeds approximately 19°C, the trustworthiness levels start to deviate. This holds true when inspecting the raw data, with the conclusion that LiRo and BedR2ndF correlate and vary more heavily depending on the time of day and outdoor temperature, whereas Hallway is more stable. To illustrate this we select the timespan of late June 2013, when the outdoor temperature at the location of the house was over the adjusted indoor temperature, thus resulting in deviations in the level of trust. Contrary, the levels of trustworthiness are more stable if the timespan were in, for example, October. A trustworthiness score for the weighted mean cannot be provided as this is up to the consumer of this reading to decide. However, if this were needed, the weight of each trustworthiness level should be taken into account. A straightforward function for this could be $\sum\left(E\left(\vec{b}(x_i)\right)\right)^2 / \sum E\left(\vec{b}(x_i)\right)$ for $i = 1, \ldots, n$ readings; this is the curve of the weighted mean trust in Figure 2. We stress that this is only for illustrative purposes.

4. DISCUSSION

This paper proposes a continuous method for evaluating trustworthiness of environmental measurement processes. A central aspect of trustworthiness is claimed to be the level of uncertainty. Objections on the means and validity of uncertainty are valid. Such an objection can always be raised when a method is applied on a changing phenomenon, such as the environment. For a non-dynamic (static) phenomenon, a level of trustworthiness could be acquired quantitative analysis given a formal model. However, as the environment considered as ever changing and given the lack of a formal model of this, quantitative analysis does not suffice. Yet the mathematical framework basing on Dempster-Shafter theory of evidence and Subjective Logic is sound with respect to analysing uncertainty. The proposed approach considers a dynamic level trustworthiness acknowledging that defining correctness (the model) is a serious challenge (Parnas 2010) and is impossible for informal events. Hence, as uncertainty is inherent, we argue that it must be treated in its own right without abstraction or assumption in a dynamic manner. For this, we argue that the presented method qualifies well; motivated by the initial results on the case presented in this paper.

For environmental modelling, uncertainty is inherent and it is continuously varying. Consider for example the observed temperature data as considered in this paper. For this, the spatial positioning of the sensor is critical, as some indoor locations are subject to greater variations, e.g. exposed to the sun, next to the oven, in the sauna etc. Yet, these measurement values may provide highly trustworthy readings most of the time, with deviations under specific conditions. Hence, the level of trustworthiness on a value is context-dependent. Deriving the context and reasoning on this is a research filed of its own, not considered further here. However, regardless of the context, common to methods considering trustworthiness is that the consumer of the data needs to react to variations (in quality or context) promptly, by adjusting the level of trustworthiness. The proposed method on trustworthiness is very apt for this, abstracting the reason of variation and acknowledging that the source may not be aware of its decreased ability to provide trustworthy data. The only restriction recognised on the method is that the logical topology of the measurement processes needs to be a polytree (Neovius 2012), i.e. an undirected acyclic graph.

Criticism regarding the output of the method as some value without semantics is void. This is because the expectation value in SL maps any opinion to a dogmatic (probabilistic) value. Questioning what the weighted mean actually means may also arise. As for uncertainty, we cannot give a definitive answer, having to state that the weighted mean output is the most probable measurement value with respect to the parameters and their a priori behaviour. Here the parameters include decay (λ) and all the other interpretations made by the method.

5. CONCLUSION AND FUTURE WORK

This paper presented a novel method for calculating with uncertainty on continuous and ever changing values. The method is based on Dempster-Shafer theory of evidence and Subjective Logic. The central concept is that of an experience that is represented as a four-tuple, functioning as the recorded entity. From a set of such experiences, we show how an abstracted score tuple ($\alpha^{Abs}, \beta^{Abs}$)

as defined by function (1) may be derived by computationally light summation. The abstract score may be visualised as a Beta probability density function. Moreover, the abstracted score $(\alpha^{Abs}, \beta^{Abs})$ can be transformed into the three-valued opinion (ω) by a mapping function (2). The opinion representation feature many sound means of treating networks of agents with assigned trustworthiness scores in the Subjective Logic.

Scaling the method from an indoor environment to a larger domain is possible. As part of future work we plan to apply the method to evaluate vast amounts of data, e.g. city-wide observations capturing the microclimate, participatory sensing and ultimately as part of the social computer (Giunchiglia and Robertson 2010). From a mathematical point of view, we see no obstacles for this; computationally the method is light. Socially however, difficulties are many. Likely difficulties arise in the evaluation of loosely coupled data in case a stance needs to be taken on whether or not similar data can be used for evaluation. In such cases, the preferences of the perceiver are also a factor as is the preserving of intimacy of the provider. Thus, the challenges are great but so are the possibilities.

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