Adaptive Experience-Based Composition of Continuously Changing Quality of Context

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Abstract—Contemporary systems increasingly rely on information provided by autonomous agents. The autonomous agents provide inherently inaccurate information due to, for example, rounding, calibration error or subjectivity. Moreover, the level of information inaccuracy may change without notice. Regardless the reason of the inaccuracy, a system relying on such information needs to adapt to the quality of the momentary information. In this paper, we propose a method for this adaption. The method bases on evidence theory and probability theory to compose a ground truth from disjoint information in a proposition. This ground truth is used to evaluate the disjoint information and determine this experience's score. Each experience adds to the history of experiences in an agent, i.e., to the amount and character of evidence an agent has on another's performance. Moreover, the method features a forgetting parameter facilitating adaption in case of, for example, maintenance to the providing agent. The method output is one parameter denoting the level of confidence the system certifies the composed information with. The presented method is validated by a case study on a dataset of in-house temperature data.

Keywords-Experience-based trust; adaptive systems, reputation-based trust, evidence theory; uncertainty, trust model.

I. INTRODUCTION

In the era of big data and cloud computing, a system manifests in an application providing a human user a means to perform a task [1 – 2]. The device, in this case, functions as the mere portal to the user's application space and information enhanced environment; with the application providing the user-interface and the gateway to the Internet scale information enhanced environment. This information enhanced environment is stored, maintained, updated and provided by autonomous agents connected 'all the time everywhere' [3]. Hence, the application produces automated transactions in the Information Revolution [4] without any conception of the momentary level of confidence that may justifiably be placed on the information it relies on.

In this setting, each piece of information is subject to the context in which it was created. For example, consider a measurement value of an elementary sensor, the information imperfection includes: imprecision when being inexact, ambiguity when non-unanimous data are available, error when a mismatch is found between the actual and reported value and unknown when the properties are not fully known [5]. On these, van Bunningen et al. [6] note that information dependent on the context of its measurement is continuously changing, imperfect and *uncertain*. In wireless sensor networks, Nakamura et al. [7] list reasons including variations of temperature, pressure, electromagnetic noise, radiation and conclude that sensors' measurements may be rendered imprecise (or even useless). These inaccuracies and ambiguities, being the context of the information, count for the inherent inaccuracy that all contextual information is subject to.

This inaccuracy is captured by the concept of Quality of Context (QoC) [8]. In QoC, context is defined as "…*any information that can be used to characterize the situation of an entity…*" [9] and it describes the contextual information's distance from the real world [10]. QoC is defined on the information, not the provider, with parameters including: precision, probability of correctness, *trustworthiness*, resolution and up-to-dateness [8]. Of these, trustworthiness is noted as the rated certainty of the other QoC parameters. That is, trustworthiness is the information providing agent's level of certification on the information it provides. Thus, the parameter of trustworthiness outlines a level of confidence and (un)certainty in the information.

McKnight and Chervaney [11] define the trusting intension as "*The extent to which one party is willing to depend on the other party in a given situation with a feeling of relative security, even though negative consequences are possible*". From this definition we note that the parties are *agents*, called *trustor* and *trustee*, where a trustor willingly trusts a trustee despite a risk of a negative outcome. Thus, trust is valid only when something can go wrong. Moreover, as the feeling of relative security may vary by trustor and situation, the level of trust is subjective. With respect to confidence, (un)certainty and the ever changing context, we further stress that a level of trust needs to continuously adapt. For this, we use Dempster-Shafer (DS) theory of evidence and its extension called Subjective Logic (SL).

SL is a probabilistic logic originally proposed by Jøsang [12]. It may be used to analyse Bayesian networks [13]. SL provides a computational logic for calculating subjective trust by a three-valued parameter called an opinion. Moreover, it features second-hand evidence. A mapping function between

a SL opinion and the Beta probability density function (Bpdf) have been devised [12] [14]. To provide the input to SL and Bpdf, we outline an *experience* in line with Teacy [15] and Neovius [16] as a four tuple. Each experience is a piece of evidence of an agent's evaluated transaction with another agent. The set of experiences is the history of an agent's evaluated transactions. Hence, the *experience-based* trust; sometimes used interchangeably with the concept of reputation-based.

In this paper, we outline the logics of a trust calculation and present a computational model for adaption by trust levels. The model's output is a tuple, called the abstract score that complies with the Bpdf type and thus, with SL framework. We extend on previous work [17] by the generality, motivating and presenting the mathematical treatment of uncertainty in DS theory and by highlighting the adaptive behaviour. Moreover, we elaborate on the history of experiences; motivating the experience-based approach. This is also the main contribution of this paper; as the history of experiences builds up and decays, the level of trust adapts. Based on the findings, we claim that the adaptive behaviour enables correction of inherently inconsistent and inaccurate information. To the best of our knowledge, this paper is the first to study the combination of context, adaption and subjective trust from a mathematical-logical point of view. In addition, this paper elaborates on the limitations of the approach by presenting assumed properties of a trust relation. Thus, this paper takes a more general view on experience-based trust and uses the in-house case study as validation; as opposed to the case study walk-through provided in previous work [17]. The most severe limitation of the approach is the need of a ground truth. If such a ground truth cannot be devised, the method is void. However, a ground truth may be defined by a human evaluation, derived indirectly or, as in the case study, derived as a variant of redundant measurements.

The general plot of this paper is depicted in Fig. 1 featuring three kinds of agents, inspired by related work [18] - [22]. Top left agent observes a property of a phenomenon transforming a real world event to a software event. Realistically, this is a temperature sensor. Bottom left, in the middle and bottom right are agents that rely on observations and other providing agents for supplying information needed for inference. The inference may, or may not give rise to triggering an actuator (top right) transforming the software event back to a real world event. We note, however, that the inference is out of the scope of this paper.

The reminder of this paper is organized as follows: In Section II, we outline the basics for evidence theory. Section III describes the experience-based trust including the level of trust, experiences, score type, decay function and a means to abstract the history of experiences to outline a subjective level of trust. Section IV describes the case study and highlights a clear point of adaption. Section V concludes the paper followed by references in Section VI.

II. DEMPSTER-SHAFER THEORY OF EVIDENCE

As noted, a level of trust encompasses the level of confidence as dependence and reliance and a level of (un)certainty. For this, DS theory of evidence [23], also known as a belief function fits well. A belief function relies on a set of known outcomes ζ, called the frame of discernment. This frame denotes the exclusive and exhaustive outcomes, e.g., in case of determining the colour of a ball, all possible colours. On a frame, the mass (certainty) $m: 2^\zeta \rightarrow [0, 1]$ denotes the level of evidence for each outcome. The probabilistic view on the evidence assigns m to each element 2^ζ and is called basic belief assignment where $m(\emptyset) = 0$ and $\sum_{A \in 2^\zeta} m(A) = 1$. This additivity denotes that an evaluation is performed each time. In case the observer is uncertain, e.g., in case a red-green colour blind person evaluates a red ball on mass space $\zeta = \{x_{red}, x_{green}, x_{blue}\}$ the evaluation is $(\{x_{red}, x_{green}\})$. That is, the evaluation provides a piece of evidence for "not x_{blue}".

In addition to the mass m, the belief bel is defined $bel(A) = \sum_{B \subseteq A} m(B)$. Hence, bel denotes the 'certainty' or 'evidence' in a set as the sum of masses of its subsets, e.g., $bel(\{x_1, x_2\}) = m(\{x_1\}) + m(\{x_2\}) + m(\{x_1, x_2\})$. The mass of the total set $m(\zeta)$ may not be 0, i.e., $m(\{x_1, x_2, x_3\}) \neq 0$. Realistically, this is the case when a blind person would evaluate a ball's colour. Plausibility pl denote the 'max probability'; or that 'there is evidence against this proposition'. Thus, $pl \geq bel$ and $pl(A) = \sum_{A \cap B \neq \emptyset} m(B)$; the sum of non-empty intersecting masses or more conveniently, $pl(A) = 1 - bel(\bar{A})$ where $\bar{A}$ denotes complement of A. Thus, belief and plausibility provides the
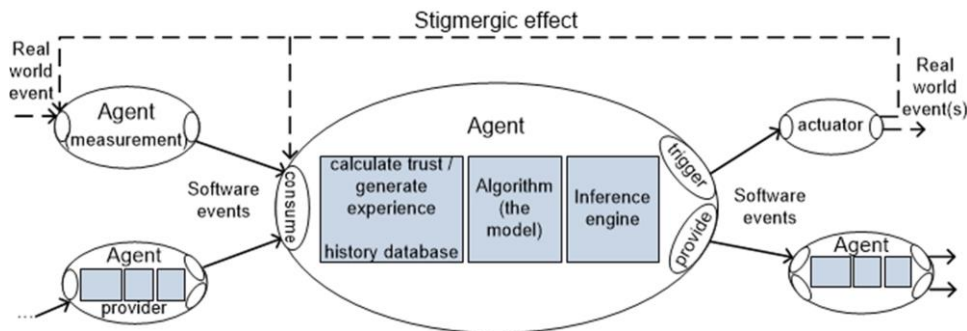

Figure 1. The adaptive agent

lower (*bel*) and upper (*pl*) bounds of evidence with the *uncertainty* as the difference between these. Consequently, DS theory provides a foundation for evidence-based trust. Readers interested in this relation and its theoretical foundations with trust are directed elsewhere [24] [25].

III. EXPERIENCE-BASED TRUST

An experience is an evaluation generated by a trustor *A* on a transaction it had with a trustee *B*. Obviously, when the evaluation is subject to bias or appreciation, *A*'s evaluation is *subjective*. This implies that if agents *B* and *C* share an experience on a matter, *A*'s and *C*'s evaluations may justifiably be different without anyone "lying". Moreover, *A*'s trust in *B* does not indicate anything of *B*'s trust in *A*, hence trust is *asymmetric*. On the history of experiences, it is motivated that more recent experiences weighs heavier. Hence, the level of trust is *incomplete*, i.e., it is non-absolute and non-dogmatic. This implies that trust *evolves over time* and is non-monotonic. Non-monotonicity fundamentally differentiates experience-based trust from statistical model checking methods. Moreover, as *B* may provide information regarding disjoint frames, e.g., observing the colour of a ball and its elasticity, the trust level is *proposition specific*. That is, given disjoint ζ_1 and ζ_2, *A*'s level of trust on *B* in ζ_1 and ζ_2 may be different [26]. The proposition specificity also encapsulates a frame of discernment from other frames, thus, voiding cross-layer effects of unforeseen dependencies.

The property of trust transitivity is discussed in literature [13] [27] - [29] with motivations for and against. In the presented method, positive trust is considered transitive, but negative trust (distrust) is not [30]. That is, if agent *A* trusts *B* and *B* trusts *C*, then by transitivity *A* trusts *C*. If distrust were transitive solving whether your enemy's enemy is your friend [25] would be required, i.e., if *A* distrust *B* and *B* distrust *C*, does this indicate that *A* trusts *C*? This motivates our view that distrust indicates not to trust any information provided by a distrusted agent, here *B*. More on these trust properties and their foundations is found elsewhere [27].

A. The Level of Trust

Let a trust relation derived from experiences between two agents, *A* and *B*, be denoted by $_T$. Moreover, let the level of trust be denoted ω. Thus, agent *A*'s trust in *B* in a proposition is denoted $A_{\zeta T\omega}B$. Whenever the proposition $\zeta \subset 2^{\zeta} \wedge \zeta \neq \emptyset$, this level is subadditive. A subadditive level of trust features the levels of confidence as (dis)belief and (un)certainty. Here, uncertainty must not be confused with (dis)belief, also known as distrust [31] [32]. Moreover, the uncertainty enables implementation of decay reducing evidence without subverting the experience.

In addition to the level, we distinguish between first-hand and second-hand trust levels as in SL [12]. A first-hand trust level is derived from first-hand direct (*d*) experiences with the trustee in a proposition. A second-hand trust level is an indirect (*i*) level, where referral agents' experiences are used to strengthen an agent's evidence. Moreover, trusting an

agent as a referral is a meta proposition in its own right; thus we consider trust either referral (*r*) or functional (*f*). Indirect functional trust when $A_{\zeta Tdr\omega}B$ and $B_{\zeta Tdf\omega}C$ between agent *A* and *C* is denoted $A_{\zeta Tif\omega}C$, depicted in Fig. 2.
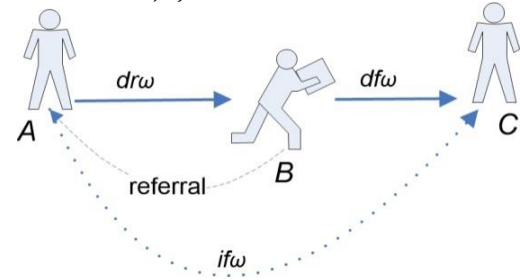

Figure 2. Trust transitivity

B. The Experiences

In order to derive a level of experience-based trust, we need to define the experience type. The type is defined a four tuple $(\delta, \epsilon, \zeta, \eta)$, inspired by Krukow [33] Teacy et. al [15] first introduced in Neovius [16]. The elements of the tuple are: $\delta \in \{\langle agents \rangle\}$, ϵ as the datum, $\zeta \subseteq \{\langle frame \rangle\}$ and $\eta \in \{\langle score \rangle\}$. Realistically, the datum ϵ is time. An experience generated by agent *A* on *B* at *x* in proposition *y* with score *z* is denoted $Exp^A(\epsilon) = (B, x, y, z)$. The history of agent *A*'s experiences $Exp^A(\epsilon_i)$ for *i* = 1, …, *n* is a set of disjoint experience, i.e., $\{(\delta, \epsilon, \zeta, \eta)\}$. Adding a new experience $(\delta, \epsilon_0, \zeta, \eta)$ at datum ϵ_0 to the history is straight forward $Exp^A(\epsilon_j) = (\delta, \epsilon_0, \zeta, \eta) \cup \{(\delta, \epsilon_i, \zeta, \eta)\}$ where *j* = 1, …, *n*, ϵ_0.

On this experience type, projections provide specific experiences. Consider agent *A* to have interacted with *B*, then experiences on *B* at ϵ are projected by $Exp^A(B, \epsilon) = \{(B, \epsilon, \zeta, \eta)\}$ where $\{(B, \epsilon, \zeta, \eta)\} \subseteq \{(\delta, \epsilon_i, \zeta, \eta)\}$. Projecting on any element is done similarly, e.g., $Exp^A(B, \epsilon_p, x) = \{(\epsilon_i, \eta)\}$ for $x \subseteq \zeta$ and $\epsilon_i \leq \epsilon_p$ for *i* = 0, 1, … *p*.

C. Type of Score

We propose a versatile score type as a tuple (*sat*, *usat*) for satisfactory and unsatisfactory. Here $sat, usat \in [0, 1]$ and $sat + usat \leq 1$. Subadditivity is fundamental for implementing uncertainty and decay without subverting the semantics of the experiences' score. A score is dogmatic whenever $sat + usat = 1$. Coarsening a multinomial proposition $|\zeta| \geq 3$ to a binomial $|\zeta| = 2$ is done by summation, i.e., considering the coloured balls $\zeta = \{x_r, x_g, x_b\}$ with $Exp^A\left(A, \epsilon, (x_r, x_g)\right) = \{(\epsilon_i, (sat, usat))\}$ providing the evidence against x_b. Related work considering a similar score type includes Noorian et al. [34] model.

With this score type, vacuous experiences are expressed with the score (0, 0); dogmatic scores (the probabilistic view) $sat + usat = 1$; and absolute scores (binary view) when (*sat*, *usat*) = (0, 1) or (*sat*, *usat*) = (1, 0). Thus, a score is valid with a certainty of $sat + usat$, e.g., given *sat* = 0.3 and *usat* = 0.5, the certainty is 0.8. From this, uncertainty *u* is easily

derived, $u = 1 - sat - usat$ as is the dogmatic expectation value of satisfyability as $sat / (sat + usat)$.

D. Decay of an Experience Score

Decay of an experience score is the act of forgetting or forgiving. This is fundamental in case of transient faults or maintenance / update on the data provider having an effect on the data quality. Fundamental for decay is that it must not subvert the score of experiences, only reduce its weight [34]. Let the decay factor be denoted by λ where $0 \leq \lambda \leq 1$. Decay relies on a continuous factor by which it decays, here datum ϵ. We define the general decay function d at datum ϵ_m called d_{ϵ_m} on an experience $Exp^\delta(\epsilon_i)$ where $\epsilon_i \leq \epsilon_m$ as:

$$d_{\epsilon_m}\left(Exp^\delta(\epsilon_i)\right) = (\delta', \epsilon_i, \zeta, \lambda^{\epsilon_m - \epsilon_i} * \eta) \qquad (1)$$

Dually, this decay may be applied on the history of experiences where $\epsilon_n = 1, \ldots, m$ and $\epsilon_n \leq \epsilon_m$:

$$d_{\epsilon_m}\left(Exp^\delta(\epsilon_n)\right) = \{(\delta', \epsilon_n, \zeta, \lambda^{\epsilon_m - \epsilon_n} * \eta)\} \qquad (2)$$

With equations (1) and (2), the closer λ is to 1 the slower the speed of decay with $\lambda = 1$ indicating no decay at all. No decay is motivated in, among others, quantitative statistical analysis. Contrary, $\lambda = 0$ indicates complete decay as in a stochastic process [35].

E. Abstracting Experiences

To calculate with the experiences, the projection on the experiences' scores needs to be composed. We call this an abstract experience Abs at datum ϵ_m, hence Abs_{ϵ_m}. If this abstraction is done on decayed experiences, such a composition outlines the momentary decayed score, the abstracted score $absscore$. We define this for $\epsilon_n = 1, \ldots, m$ and $\epsilon_n \leq \epsilon_m$:

$$Abs_{\epsilon_m}\left(Exp^\delta(\epsilon_m)\right) = (\delta', \epsilon_m, \zeta, \sum_{d_{\epsilon_m} Exp^\delta(\delta', \epsilon_n, \zeta)} \eta) \quad (3)$$

With this, $Abs_{\epsilon_m}\left(Exp^\delta(\delta', \epsilon_m, \zeta)\right)$ score $absscore \in \mathbb{R}^+$ relies on summation defined ($abssat$, $absusat$).

Not surprisingly, as $Abs_{\epsilon_m}\left(Exp^\delta(\epsilon_i)\right)$ denotes the $absscore$ decayed at datum ϵ_m, an updated abstract view $Abs_{\epsilon_{m'}}\left(Exp^\delta(\epsilon_i)\right)$ where $m \leq m'$ is a recursive function [36] whenever the decaying factor is universal, continuous and applied on all experiences locally, e.g., decay by time. Hence, updating $Abs_{\epsilon_m}\left(Exp^\delta(\epsilon_i)\right)$ to $\epsilon_{m'}$ where $\epsilon_{m'} = \epsilon_m + i$ is straightforward:

$$Abs_{\epsilon_{m'}}\left(Exp^\delta(\epsilon_i)\right) = \delta', \epsilon_{m'}, \zeta, \left(Exp^\delta(\delta', \epsilon_{m'}, \zeta, \eta) + \right.$$
$$\left. Abs_{\epsilon_m}\left(Exp^\delta(\delta', \epsilon_m, \zeta)\right) * \lambda^i\right) (4)$$

Here, $Exp^\delta(\delta', \epsilon_{m'}, \zeta, \eta)$ is the new experience. Thereby, abstraction is an irreversible function that provides some level of privacy that decay enhances on. This abstracted experience with a score ($abssat$, $absusat$) may be depicted as a Bpdf and is, hence, mappable to an opinion in SL. Examples may be found elsewhere [36] - [38]. Computationally, the method is very light thus, facilitating scalability.

IV. IN-HOUSE CASE STUDY

As proof of concept, we have applied the presented method on an in-house temperature measurement system. This system encompasses a dataset of four disjoint points of temperature measurement with 10 seconds interval over a time span of one year; a total of ~12 million readings. We filtered the dataset from impossible measurements such as -49950°C by disregarding readings outside the interval $[-50°C, 50°C]$. We used $\lambda = 0.95$ as in eq. (1, 2, 4).

The purpose is to model an "in-house temperature agent" that composes the disjoint measurements to the most probable temperature and certifies this by a level of trust. For this, the method provides a weighted mean temperature (*wmt*) and a weighted level of trust (*wlt*). The wlt defines the momentary level of trust that the in-house temperature agent certifies the wmt with that sets the ground truth. An elementary temperature measurement experience's score is generated by the three-sigma rule of standard deviation from the normal distribution of the posterior wmt. Thus, initially with no experiences (equal trust on all measurements) the wmt is the arithmetic mean.

A snapshot of the analysis is depicted in Fig. 3. The abbreviations in the legend of Fig. 3 are as follows. On the left scale: FiPl = fireplace sensor, LiRo = living room sensor, wlt, Hallway = hallway sensor, BedR2ndF = bedroom 2nd floor sensor; and on the right scale: Mean temp. = arithmetic mean temperature in °C, Daily mean = the daily mean temperature outdoor in °C and wmt in °C. The primary vertical axis denotes the trust level, the secondary vertical axis denotes the temperature °C, and the horizontal axis denotes time as mm.dd.yyyy hh:min.

Temperature	Measurements (4000sec. interval) in °C						
	Arith. mean	*LiRo temp*	*EnWa temp*	*B2F temp*	*FiPl temp*	*wmt*	*wlt*
6.15.2013 3:13 –3:46	21,68	23,55	22,75	23,26	17,18	23,19	0,72
	26,40	23,55	22,42	23,26	36,37	23,08	0,79
	17,77	23,55	22,42	23,26	1,8	23,08	0,80
	18,82	23,55	22,42	23,26	5,67	23,08	0,81
	21,60	23,55	22,42	23,26	17,18	23,08	0,80
	21,64	23,55	22,55	23,26	17,18	23,12	0,81
...	...	...	...	...	...	...	...
6.27.2013 13:37 – 6.27.32013 14:26	26,65	29,35	26,36	29,88	21,02	28,59	0,77
	28,29	23,43	26,36	27,01	36,37	25,64	0,76
	24,45	23,43	26,36	27,01	21,02	25,67	0,75
	24,44	23,43	26,29	27,01	21,02	25,66	0,75
	24,45	23,43	26,36	27,01	21,02	25,69	0,71
	21,56	23,43	26,29	27,01	9,51	25,69	0,66
	21,58	23,43	26,36	27,01	9,51	25,69	0,74
	23,48	23,43	26,29	27,01	17,18	25,68	0,74

TABLE I.   A SAMPLE OF TEMPERATURES AND TRUST LEVELS

Fig. 3 reveals that FiPl is malfunctioning by a close to 0 level of trust. Table 1 depicts this inconsistency as a more specific snapshot. Fig. 3 also reveals 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
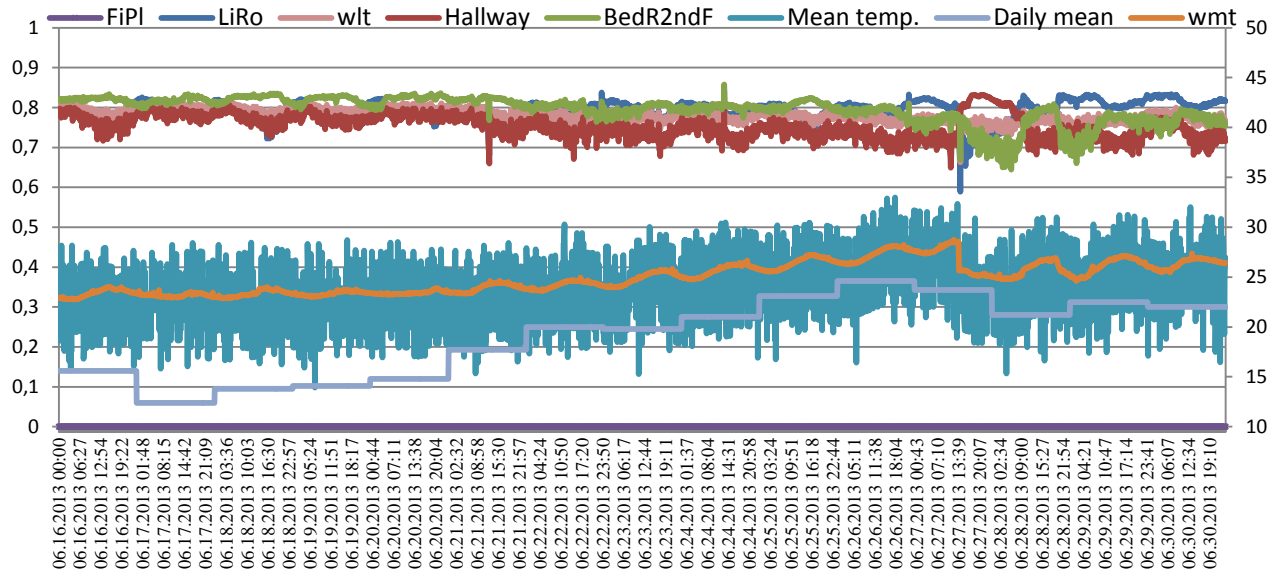
Figure 3. Indoor temperature and measurement processes' trust levels with λ = 0.95 (June 2013)

BedR2ndF correlates and vary more heavily depending on the time of day and outdoor temperature, whereas Hallway is more stable. To illustrate this, Fig. 3 plots a timespan of late June 2013, when the outdoor temperature at the location of the house was higher than the adjusted indoor temperature resulting in deviations in the levels of trust.

Notable in the graph is the sudden drop of trust levels of LiRo, BedR2ndF and the relative increase of Hallway points of measurement 06.27.2013 at around 13:40. The reason for this is a thunder storm. Fig. 3 plots this as a drop in wmt and inconsistency in trust levels in a reasonable manner only to recover gradually, with a lower λ the recovery is faster. Hence, the system adapted to the change in information quality. Moreover, it reasonably dropped the weighted mean temperature and the weighted mean trust during the inconsistent event of the thunder storm.

V. CONCLUSIONS

The trend in contemporary computerised systems is towards agent and system autonomy. Concepts like system of systems, software as a service and many alike are proofs of this. In all these cases, the application performing a task for a stakeholder is assumed to rely on information provided by agents not in its control. As there is no guarantee on the providing agents' reliability, a consuming agent may only adapt to the momentary best-effort perception on the providing agent. A survey may be found elsewhere [39]. This paper motivates, define and use a level of trust as the basis for adaption.

The approach is implemented on a dataset of four temperature sensors. Though this dataset is very well fitted for this particular approach, the underlying mathematics is described in detail sufficient to be applied on related problem scenarios. We believe that the results will be good if done; an

issue that remains as future work. Moreover, the method scale as it is computationally light. In addition, the case-study sensors could be replaced by an adaptive agent as in Fig. 1, e.g., being provided by a service.

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