Context Fusion through Imprecise Reasoning

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Abstract - **Pervasive computing is an emerging computing paradigm that provides intelligent context-aware applications. Such applications handle contextual information in order to determine the current user's situation. Contextual information is typically inaccurate (e.g., noise of sensor readings). A novel context fusion engine* that models, determines and reasons about the current user's situation is proposed. This engine, based on Dynamic Bayesian Networks and Fuzzy Logic, deals with the reliability of sources and approximate contextual reasoning.**

Key words - **context modeling, context fusion, sensors reliability, probabilistic inference, approximate reasoning, location estimation**

I. Introduction

Pervasive computing is emerging as the future computing paradigm in which infrastructure and services are seamlessly available anywhere and anytime. Pervasive computing applications require support for managing imprecise context. In such applications, observations are recorded from a number of sensors. The context estimation is characterized by imprecise knowledge, e.g. missing information and unreliability of sources. The method of deriving high-level understanding from low-level, inaccurate sensor data is called *context fusion*.

Several methods have been proposed to deal with imprecise contextual information [1]. Approximate reasoning produces knowledge about the user's situation. The different kinds of imperfection can be handled through Fuzzy Logic (FL) [2]. However, FL is based on specific degrees of uncertainty and vagueness at context determination. Allowing a degree of fuzziness not only at the situation determination phase but also at decision making (e.g., triggering of several actions), context-aware applications become more robust and flexible.

In this paper, a probabilistic context fusion through FL is proposed. Specifically, context fusion is based not only on the joint probability over sensor data but, also, on the reliability of sources deployed on the environment. This means that, during the fusion process, a degree of confidence over the sensed / retrieved context is taken into consideration enabling more accurately reasoning about the current situation of a user (e.g. location, actions).

The paper is organized as follows: in Section II the terms context and confidence are defined, while Section III discusses the probabilistic context fusion based on Dynamic Bayesian Networks (DBNs). In Section IV, the reliability of sources is incorporated through FL in the fusion process, and in Section V, the proposed mechanism is evaluated with real context data. Section VI discusses related work and, finally, Section VII concludes the paper.

II. Context Model

A. Context Definition

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A well-known definition of context in [3] defines that "context is any information that can be used to characterize the situation of an entity. An entity is a person, place or object that is considered relevant to the integration between a user and an application, including the user and the application themselves". Our approach in context modeling is illustrated by the following definition of contextual attribute and situation.

Definition 1. Let the finite set $A(k)$ of contextual attributes a of description level k, $k \geq 0$. Such attributes constitute the context of k-level. A level of 0 ($k = 0$), denotes a non-inferential context (e.g., sensor readings). An attribute a is instantiated with a value u when referring to the proposition "a is u". Situation or situational context is defined as the k-level attribute $p \in A(k)$ with $k \geq 1$.

Situation is derived from a synthesis of attributes belonging to sets of m_i-levels with $m_i < k$. Such synthesis is a logical aggregation ($\wedge$) of n propositions "a_i is u_i", $i = 1,\ldots,n$. Specifically, a situation is the implication of conjunctive propositions that hold at a specific time and is represented by a rule of k-level, as in (1). The v value in (1) belongs to the domain set of all considered situational contexts.

$$(a_1 \text{ is } u_1) \wedge \ldots \wedge (a_n \text{ is } u_n) \rightarrow (p \text{ is } v) \quad (1)$$

where $a_i \in A(m_i)$, $p \in A(k)$, $k = (\max_i(m_i) + 1)$, $i = 1,\ldots,n$. We refer to "a_i is u_i" as the antecedent-part and to "p is v" as the consequent-part. In such model, if all observations u_i are assumed to be reliable then, we can extend the reading of "a_i is u_i" to "a_i is u_i and the observation of u_i is $reliable_i$". Fig. 1 illustrates the reasoning structure of the observed values that determine a situation.

Definition 2. Dimension $d(p)$ of the k-level situation p is defined as the number of attributes that conclude and determine p. Hence, $d(p) = n$ if p is the consequent of a k-level rule with n antecedents. By definition,($d(p) \geq d(q) \Leftrightarrow ((p \in A(k)) \wedge (q \in A(m)) \wedge (A(k) \supseteq A(m)) \wedge (k \geq m)$), which means that situation p is more specific than situation q, annotated as $p \rightarrow q$.

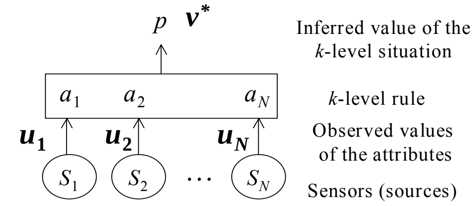

Fig. 1. Structure of situational context determination

L. Zadeh in [2] defines the fuzzy set theory as an extension of the set theory. Non-fuzzy sets only allow full membership or no membership at all, where fuzzy sets allow partial membership. In other words, an element u ∈ U may partially belong to a set. Such partial membership, called degree of membership, is represented by a membership function μ which takes values from 0 to 1, i.e., $\mu: U \rightarrow [0,1]$. Moreover, a fuzzy set A is defined as the set of pairs (membership degree, element), that is $A = \{(\mu(u), u) \mid u \in U\}$. The knowledge of the context value cannot be assessed precisely in a quantitative form. Instead, it may be assessed in a qualitative way. Hence, the use of a linguistic approach is deemed appropriate. Context may be un-quantifiable due to its nature, and may be stated in linguistic terms (*low* temperature, *high* sound and *natural* light).

B. Reliability of Sources and Context Confidence

Sensors are often inaccurate and it is important to incorporate accuracy estimation in the situational context reasoning. Knowledge about sensors accuracy can be obtained by various means, e.g. manufacturer's specifications, operating time, confidence/reliability calculation techniques. In order to estimate how confident we are on sensing a value, we define the source reliability degree for each source. Specifically, this quantity associates a degree of reliability, h, to each of the S_i sources in $\mathbf{S} = \{S_1,\ldots,S_N\}$ $i = 1,\ldots,N$. The h indicator is defined as follows:

$$h: \mathbf{S} \rightarrow [0, 1] \tag{2}$$

Consider the value u_i of the a_i attribute that corresponds to the source $S_i \in \mathbf{S}$, $i = 1,\ldots,N$. Then, confidence *conf* for the values that infer the k-level situation p is calculated as follows:

$$conf = \max_{u} [\min_{(i,j)\in N\times N}(h(S_i),h(S_j))_u], u = 1..\binom{N}{2} \tag{3}$$

Specifically, there are $\binom{N}{2}$ pairs of S_i and S_j sources in $\mathbf{S}$, i, j = 0,...,N. Hence, confidence is the maximum value of the $\binom{N}{2}$ minimum degrees derived from the h reliability of each pair of sources. For instance, for $\mathbf{S} = \{S_1, S_2, S_3\}$ with reliability values (0.2, 0.4, 0.8), respectively, the confidence value is max {min(0.2, 0.4), min(0.2, 0.8), min(0.4, 0.8)} = 0.4. According to the Certainty Factor theory [4], the analogous confidence value for the *and*-aggregation of the antecedents is the $\min_i h(S_i), i = 1,\ldots,N$.

The k-level rule that concludes a situation p and takes into consideration the reliability of the sources is defined as follows:

$$[(a_1 \text{ is } u_1) \wedge conf_1] \wedge .. \wedge [(a_n \text{ is } u_n) \wedge conf_i] \rightarrow (p \text{ is } v) \tag{4}$$

where $conf_i$ is the confidence on the observation or conclusion of the value u_i of the context attribute a_i. If $a_i \in A(0)$ then, $conf_i$ is the reliability h_i of the source a_i, Hence, the confidence on the value v of the concluded situation p is calculated by (3), given that the confidence values $conf_i$, i=1,…,n, of the a_i antecedents of the p situation have been estimated.

III. Probabilistic Fusion

We adopt the probabilistic fusion from [5], which is based on Dynamic Bayesian Networks (DBN). A DBN extends the static Bayesian Network (BN) by modeling changes of random variables over time. Random variables in a DBN are affected by variables from previous time slots. Details about BNs can be found on [10].

A. DBN Integration in Context Fusion Engine

The random variables of the DBN are (i) attributes $a \in A(0)$ (i.e., sensor readings) and, (ii) situations $p \in A(k)$ with $k \geq 1$. A situation $p \in A(k)$ can affect (i) a situation $q \in A(m)$ with $m<k$ and (ii) an attribute $a \in A(0)$ at the same time (Fig. 2). For each sensor $S_i \in \mathbf{S}$ (or a_i), i = 0,…,N, we estimate the probability distribution $P(a_i \text{ is } u_i \mid p_j \text{ is } v_j)$, $p_j \in A(k)$, $k \geq 1$. Throughout the paper we refer to the previous expression with the type $P(a_i \mid p_j)$. Moreover, for every non-root situation (situation without parent nodes), we determine the probability distribution $P(q_i \mid p_j)$, $i = 1,\ldots,d(p_j)$, with $q_i \in A(k)$, $p_j \in A(m)$, $k \geq 1$ and $m >$ k.

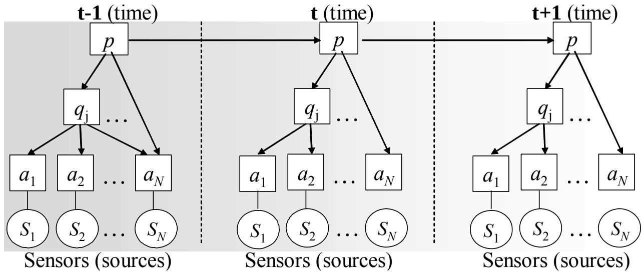

Fig. 2. DBN representing the dependencies between random variables (situations / attributes) at different time slots

B. Fusion Operator

The calculation of the conditional probability of situational contexts determines accurately the value of the situation at time t i.e., $p = p(t)$, $p \in A(k)$, as follows:

$$P(p(t) \mid q(t\text{-}1), a_{k\text{-}1}(t), a_{k\text{-}2}(t), \ldots, a_0(t)) \tag{5}$$

where $q \in A(k)$, $a_i \in A(i)$ with i = 0,..k-1. Equation (5) is the mathematical representation of the probabilistic fusion and denotes the probability of a situation at time t given the previous (i.e., at t - 1 time) value of the situation and given the values of its dependable situations and attributes at time t of lower levels. The problem of inference (fusion) is to find the situation $p(t)$ that maximizes the joint probability, that is:

$$p(t) = \arg\max_{\mathrm{i}\in \mathrm{N_k}} \{P(p_i(t) \mid q(t), a_{k\text{-}1}(t), a_{k\text{-}2}(t), \ldots, a_0(t))\} \tag{6}$$

where N_k is the number of situations of k-level. Hence, $P(p(t))$ is the probability value of the occurrence of $p(t)$ situation and we call such inference probabilistic fusion.

IV. Probabilistic Fusion With Confidence

Let p be the situation derived from the probabilistic fusion in (6). Such probabilistic fusion determines p regardless of the reliability of the contributing sources. However, $P(p(t)) = P(p)$ has to be estimated with a certain degree of confidence on sensor readings. Consider the fact that the fusion results to a high value of probability $P(p)$ but with a low confidence $conf_p$ on the sources. This could lead to a non-valid determination on the occurrence of p situation. Hence, $P(p)$ probability has to be re-evaluated taking into account the reliability of sensor readings. Such reasoning can be dealt with imprecise inference by characterizing the values of $P(p)$ and $conf_p$ with fuzzy sets. However, the proposed system has to combine $P(p)$ and $conf_p$ in an approximate reasoning manner through fuzzy inference rules, as discussed later.

The scheme for inferring a k-level situation in (4) is written in the *modus ponens* form illustrated in Fig. 3. The observations u^*_i, i = 1,…,N, are combined with the corresponding confidence values $conf_i$. The concluded value v^* for the p situation relates to the possibility of occurrence $P^*(p)$ (*confidence probability*) of p taking into account the joint probability $P(p)$ and the confidence value of each antecedent $conf_i$, $i = 1,\ldots,N$. Actually, $conf_i$ relates to fuzzy sets that describes the confidence on the u_i value.

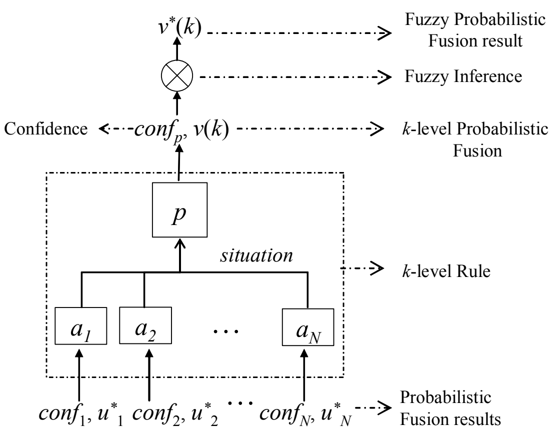

Fig. 3. Reasoning structure for fuzzy probabilistic reasoning

Three fuzzy sets A_l characterize $P(p)$ for each probability value through a set of linguistic terms $l \in \{high, medium, low\}$. A *low* $P(p)$ denotes that the system believes that, the concluded situation derives from a low probability of observation while, a *high* $P(p)$ denotes that the system assigns a high confidence on the p observation. A *medium* $P(p)$ denotes that the system is not sufficiently certain or uncertain about the observation of p. Similarly, two fuzzy sets C_l characterize the confidence values *conf* through a set of linguistic terms $l \in \{high, low\}$. A *low conf* denotes that the result (p) is computed with a low confidence i.e., low reliability of sources. *High conf* indicates that p is derived from highly reliable sources. An approximate reasoning based on Fuzzy Logic over such quantities produces a more holistic and elaborated $P^*(p)$ value.

A fuzzy implication F is a map $\Rightarrow : [0,1]\times[0,1] \rightarrow [0,1]$ of the form $x \Rightarrow y \equiv \neg x \vee y$, where $\vee$ is a t-conorm (e.g., the max-operator) and $\neg$ is a negation (e.g., $\neg x$ = 1-x). Hence, $x \Rightarrow y$ = max((1-x), y). F implication is applied over the A_l and C_l fuzzy sets and thus the improved probabilistic fuzzy value $y = P^*(p(t))$. The F implication corresponds to three fuzzy sets D_l describing a low, medium and high confidence probability $P^*(p(t))$, $l \in \{high, medium, low\}$. A fuzzy rule base is constructed of m FIR, $m > 0$. Each rule r_i (Table I(a)) contains the A_l, C_l and D_l fuzzy sets with their corresponding linguistic terms for $P(p)$, $conf_p$ and $P^*(p(t))$, $i = 1,\ldots,m$. The appropriate fuzzy value of y is then represented by the fuzzy set $Y(y)$ (see Table I(b)) depending on the input ($P(p)$, $conf_p$). Table I(c) depicts the concluded situation based on the fuzzy reasoning about the sensor readings confidence and the probabilistic fusion.

Table I (a) FIR, (b) the fuzzy set of the fusion, (c) the output of the fuzzy inference

r_1: if $P(p(t))$ is l_1 and $conf_p$ is l_1 then $P^*(p(t))$ is l_1 … r_m: if $P(p(t))$ is l_m and $conf_p$ is l_m then $P^*(p(t))$ is l_m	(a)
$Y(y) = \bigvee_{1\le i\le m} [C_{li}(P(p(t))) \wedge A_{li}(conf_p) \wedge D_{li}(y)]$	(b)
$p^*(t) = arg\max_{i\in N_k}\{P^*(p_i(t))\}$ $= arg\max_{i\in N_k}\{\mathrm{F}(P(p_i(t)), conf_{p_i})\}$	(c)

The fuzzy inference results to the fuzzy set *Y(y)*, which is *defuzzified*, and the crisp value $P^*(p(t))$ is generated. The five most essential FIR for reasoning about the probabilistic fusion and sources confidence are illustrated in Fig. 4, including *concentration* (very) and *dilution* (somewhat) modifiers.

if $P(p(\mathrm{t}))$ is *low* then y is *low*
if $P(p(\mathrm{t}))$ is *medium* and $conf_p$ is *low* then $P^*(p(\mathrm{t}))$ is very *low*
if $P(p(\mathrm{t}))$ is *medium* and $conf_p$ is *high* then $P^*(p(\mathrm{t}))$ is somewhat *high*
if $P(p(\mathrm{t}))$ is *high* and $conf_p$ is *low* then $P^*(p(\mathrm{t}))$ is *medium*
if $P(p(\mathrm{t}))$ is *high* and $conf_p$ is *high* then $P^*(p(\mathrm{t}))$ is *high*

Fig. 4. Fuzzy Inference Rules (FIR)

We call such inference as *fuzzy probabilistic fusion*, which corresponds to the enhancement of the probabilistic fusion of the p situation produced by the equation in Table I(c).The Fuzzy Inference Rules (FIR), in Fig. 4, do not describe the situation in which the probability and the confidence of the sources are simultaneously low. Instead, the confidence probability ($P^*(p)$) depends only on the value of the probability $P(p)$ (the first rule). We exclude such rule from the proposed reasoning engine because another more improved reasoning formula has to be asserted (e.g., *modus tollens* logic[1]).

The proposed inference scheme (Fig. 3) uses only one fuzzy controller at the highest level of conclusion (root situation). Specifically, the fuzzy probabilistic fusion is unique at the highest k-level i.e., $v^*(k)$. For each level m, $m < k$, the confidence $conf_{pi}$ i =1,..,N_m, $p \in A(m)$ on the values are computed according to (3), where N_m is the number of attributes of the m-level rule. Hence, the fuzzy controller applies fuzzy linguistic reasoning at level k.

V. Experimental Evaluation

A. Experimental Setup

The evaluation of the probabilistic fusion based on DBNs with fuzzy reasoning is performed using two technologies for indoor location estimation of a user: Wi-Fi Access Points (AP) and Infrared (IR) Beacons. In the following paragraphs the terms situation and location of the user are used interchangeably. The experimental setup was the 2-floor building of the Department of Informatics & Telecommunications (UoA, Greece). Each floor has dimensions of 30 X 100 meters and we used 35 symbolic locations L (*e.g., entrance, research room, etc.*). The DBN that resulted under the previously described setup is an instance of the DBN depicted in Fig. 2. During the DBN training phase, a sequence (number of samples-measurements) for all locations was compiled and fed to the system. According to the evaluation scenario a Personal Digital Assistant (PDA) was equipped with sensors for Infrared Radiation detection (IR port) and Received Signal Strength measurements (Wireless LAN adapter). Context values (sensor readings) were recorded every second. Context has the format "*a* is *u*": "AP1_RSS is -60 dBm", "IRB1 is visible".

B. Calculating the Reliability of Sources

The evaluation also takes into account the reliability of sources. In order to quantify the reliability h for each sensor Si, we used the probability distributions (Table II) that derived from the training phase of the DBN. It is obvious that, if the number of sample values (measurements) of a sensor during the training phase is distributed equally between lower and highest value for a location

[1] *Modus ponens* implies the following statement: $((p \rightarrow q \wedge p) \rightarrow q)$, whilst *modus tollens* implies: $((p \rightarrow q \wedge \neg q) \rightarrow \neg p)$

L, the probabilities in the distribution (for the specific location) would be also equally distributed. The condition of equally distributed probabilities does not offer any "real" information from the sensor as every value v has the same (approximately) probability to appear. In order to obtain better results in location estimation, the samples should not be equally distributed.

Table II. Probability distribution for the sensor AP1

	L_1	L_2	…
v_1	**0.5**	**0.0**	…
v_2	**0.3**	**0.8**	…
v_3	**0.1**	**0.2**	…
…	…	…	…

Let $V(L_i)$ be the discrete random variable which takes values from the column L_i of a probability distribution table. When the probability for a location (column) is equally distributed to all sensed values i.e., $V(L_i) = 1/k$, with $i = 1,\ldots,M$ and k is the number of the sensed values (i.e. number of rows of a probability distribution table), this means absolute ignorance on the sensed values. Hence, the higher the variance σ^2 of the random variable $V(L_i)$ the more information we obtain from that sensor for the specific location L_i (i.e., the sensor readings appear more reliable). By calculating the mean value of all variances for every location we obtain a "global" reliability h for this sensor as shown in (7).

$$h = \frac{1}{M}\sum_{i=1}^{M} \beta * \mathrm{Var}[V(L_i)] \quad (7)$$

where M is the number of symbolic locations and β is a normalizing constant since $h \in [0,1]$. IR Beacons appear more reliable on location estimation than WLAN APs. Intuitively, this is considered correct as IR Beacons have shorter range of emission thus improving the accuracy of the estimated location.

C. The Behavior of the Fuzzy Probabilistic Fusion

The system computes the probabilities for each situation (location) and the estimated location of the user is the location with the maximum confidence probability. Fig. 5 illustrates the confidence probability for the fusion techniques (i) probabilistic fusion using static BNs, (ii) probabilistic fusion using DBNs and (iii) fuzzy probabilistic fusion using DBNs. In the first case we do not take into consideration the previous location of the user for the estimation. The mean value of confidence probability is 73%. Through the use of DBNs the mean value of probability increased to 85%. Finally, in the third case, where the reliability of sources is taken into account, the confidence probability reaches to 91%.

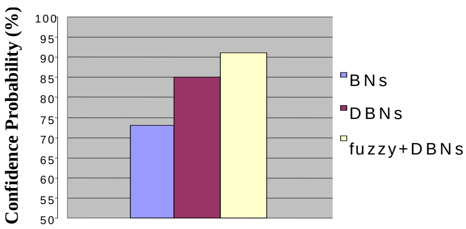

Fig. 5. Mean confidence probability of the system

Obviously, the confidence probability based on the reliability of sources assumes better values i.e., the system is sufficiently certain in order to determine a situation context. It should be noted that, the fuzzy probabilistic fusion assumes better performance when the probability is close to 0.5. (i.e., the system is not sufficiently certain about the inferred situation).

VI. RELATED WORK

There are many pervasive computing systems that use sensors readings and fusion techniques. Specifically, Location Stack [6] employs such techniques for positioning. The inability of supporting mobile devices with limited capabilities and the location, only, estimation are of the main drawbacks. The location estimation discussed in [5] based on DBN utilizes data from sensors of different technologies to infer user location. But, context-awareness is not only location estimation and spatial awareness. Many situational context models [7] appear in the situation awareness literature. Certain models are capable of reasoning about situational context knowledge [8]. Significant work in [9] deals with situational context recognition through data fusion techniques.

VII. CONCLUSIONS AND FURTHER WORK

In this paper we presented a novel context fusion engine, which exploits data from sensors or lower level contextual information in order to estimate the current user situation. A set of fuzzy inference rules are adopted in order to reason about a more elaborated fusion result based on reliability of sources. An experimental evaluation of the engine proved its capability for situational context inference. In addition, a method for calculating the reliability of sources was introduced. Besides context representation, fusion, and reasoning, the need for adaptive intelligent applications is extremely important in PCEs. A system that infers multiple simultaneous situational contexts from fusion of diverse contexts is very important. Finally, a fuzzy representation of the context attributes, the adoption of the Generalized BNs (not crisp variables) and the integration of additional information to the estimation of the sensor reliability h are future research topics.

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