Context Fusion: Dealing with Sensor Reliability

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Abstract

Context-aware applications sense, combine and reason about contextual information in order to determine and adapt to the current user's context. A very important problem associated with context is the inherent ambiguity and inaccuracy. Contextual information is typically pervaded with imperfect sensing (e.g., noise of sensor readings). A novel context fusion model that represents, determines and reasons about context based on the reliability on sensor readings is proposed. This model adopts Dynamic Bayesian Networks and Fuzzy-Set theory in order to deal with the reliability of contextual data at the context inference phase.

1. Introduction

Context-aware applications require support for managing imprecise context. In such applications, contextual information is captured from numerous sensors. Therefore, the context estimation is characterized by imprecise knowledge, e.g. missing information and unreliability on sensor readings. The method of deriving high-level understanding of context (e.g., user situation) from low-level, inaccurate contextual data is called *context fusion*.

Approximate context reasoning produces knowledge about the user's context. However, different kinds of imperfection (e.g., uncertainty, sources reliability, missing information) can be handled through the framework of the Fuzzy Logic (FL) [1]. FL is based on specific degrees of uncertainty and vagueness for representing and inferring context.

In this paper, we move beyond a simple data fusion operation. We propose a probabilistic context fusion, which takes into consideration the reliability of sources. The major contribution of the paper is the combination of the context fusion results with the estimated reliability on the sensed contextual data. Probabilistic 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 account enabling more accurately context inference (e.g. inference of the current user location).

The paper is organized as follows: Section 2 defines the terms *context*, *reliability* and *confidence*, while Section 3 discusses the probabilistic context fusion based on Dynamic Bayesian Networks (DBN). In Section 4, the reliability of sources represented through FL is incorporated in the fusion process, and in Section 5, the proposed mechanism is evaluated with real contextual data. Section 6 discusses related work and, finally, Section 7 concludes the paper.

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2. Context Representation

2.1. Context Definition

In order to render context-aware applications capable of sensing, combining and inferring imprecise context, a context model has to be adopted. Such model represents imprecise context by using various degrees of vagueness. Therefore, a well-known definition of context in [2] is 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 definitions of *contextual attribute*, *situational context* and *reliability of sources*. Further reading about context models can be found in the review in [3].

Definition 1: Let the finite set $\mathbf{P}(n) = \{p_1(n), \ldots, p_N(n)\}$ of contextual attributes $p_i(n)$, $i = 1, \ldots, N$ of detail level n, $n \geq 0$. Such attributes constitute the current *context* of n-level (e.g., motion, lightness). The set of attributes belonging to $\mathbf{P}(0)$ (0-level) represents *ground* context, i.e., context that cannot be inferred by attributes belonging to $P(0)$ (e.g., sensor readings). The value /

instance of contextual attribute of n-level refers to a set of *contextual instances* $v \in \mathrm{Dom}(p_i(n))$.

Definition 2: *Situational context* is defined as the n-level context with $n > 0$. The situational context $p(n) \in \mathbf{P}(n)$, $n \geq 1$ derives from a logical synthesis of K attributes $p_i(k_i) \in \mathbf{P}(k_i)$, $i = 1, \ldots, K$, $k_i < n$. $p(n)$ is represented by the K-ary relation from a subset of the Cartesian product $\mathbf{P}_1(k_1) \times \ldots \times \mathbf{P}_K(k_K)$ of K sets of attributes, where k_i is the level of the i^{th} set. If such relation is a logical *and*-aggregation ($\wedge$) of attributes then situational context is the *implication* ($\rightarrow$) of conjunctive attributes that hold true at a specific time, i.e., $\wedge_i(p_i(k_i))$, $i = 1, \ldots, K$. The K-ary relation can be represented as the *antecedent*-part of the *context inference rule* in (1) and the inferred $p(n)$ as the *consequent*-part. $p_i(k_i)$ may be read as "$p_i(k_i)$ is v_i" or simply "p_i is v_i", where $v_i \in \mathrm{Dom}(p_i(k_i))$. $p(n)$ is concluded by a higher level set with $n = \max\{k_i\} + 1$, $i = 1, \ldots, K$.

$$(p_1(k_1) \text{ is } v_1) \wedge \ldots \wedge (p_K(k_K) \text{ is } v_K) \rightarrow (p(n) \text{ is } v_n) \quad (1)$$

The Fuzzy-Set theory in [1] is defined 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, a fuzzy set $\mathbf{A}$ is defined over a subset of a universe of discourse $\mathbf{U}$ through a *membership function* $\mu_{\mathbf{A}}: \mathbf{U} \rightarrow [0, 1]$. An element $v \in \mathbf{U}$ belongs to $\mathbf{A}$ to a certain degree $\mu_{\mathbf{A}}(v)$. The higher a value of $\mu_{\mathbf{A}}(v)$ the higher degree of membership of v to $\mathbf{A}$. $\mathbf{A}$ is represented as $\mathbf{A} = \{\mu_{\mathbf{A}}(v_1) / v_1 + \ldots + \mu_{\mathbf{A}}(v_n) / v_n\}$ if $\mathbf{U}$ is measurable, $v_i \in \mathbf{U}$, $i = 1, \ldots, n$. A contextual instance may be un-quantifiable due to its nature and can be represented by a fuzzy set. Hence, if $v^* \in \mathrm{Dom}(p)$ be a sensed value (observation) for the v term related to p attribute then, the *degree of fulfillment* ($\in [0,1]$) of the "p is v" proposition is defined as $Pos(p \text{ is } v \mid v^*)$, i.e., the possibility of "p is v" given the observation v^* and equates to $Pos(p \text{ is } v \mid v^*) = max_u(min(v(u), v^*(u)))$, $u \in \mathrm{Dom}(p)$. Moreover, *granularity* $d(p(n))$ of the n-level $p(n)$ is defined as the number of attributes that determine $p(n)$. Hence, $d(p(n)) = K$, if $p(n)$ is the consequent of the rule in (1) with K antecedents. By definition, $d(p(n)) \geq d(p(m)) \Leftrightarrow n \geq m$. Granularity denotes the detail level of a context, i.e., the higher the granularity is, the more information the situational context conveys.

Example: Consider the situational context p = *user is attending to a conference* of level $n = 2$. p can be a synthesis of q = *user is located in a conference room* ($n = 0$) and φ = *user is presenting a report in the conference room* ($n = 1$); q is a ground context while φ can be inferred by the attributes: user location, environmental illumination and noise, a galvanometer for sensing touch, a three-axis accelerometer and the projector activity. Hence, the context inference rule for p could be $\varphi \wedge q \rightarrow p$, or specifically, *user* is *located in a conference room* $\wedge$ *user* is not *alone* $\wedge$ *user* is *standing still* $\wedge$ *environmental illumination* is *dark* $\wedge$ *environmental noise* is *low* $\wedge$ *projector* is *active* $\rightarrow$ situational context is *attendance to a conference*.

2.2. Reliability of Sources

Sensors are often inaccurate and it is important to incorporate accuracy estimation in (1). 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 contextual instance, we define the *source reliability*, h, of a source. This quantity associates a degree of reliability to each of the S_i sources in $\mathbf{S} = \{S_1, \ldots, S_L\}$, $i = 1, \ldots, L$, defined in (2). A value of 0 denotes that, the sensor readings are not considered reliable, while a value of 1 denotes the opposite. It is worth noting that, the reliability of each source is not necessarily fixed, but it may change over time, e.g., the sensor measurement accuracy may vary in different weather conditions.

$$h: \mathbf{S} \rightarrow [0, 1] \quad (2)$$

2.3. Confidence of Sources

Consider the instance v_i of the p_i attribute that corresponds to the source $S_i \in \mathbf{S}$, $i = 1, \ldots, L$. Then, the *degree of confidence*, *conf* for the instances that infer the n-level situational context $p = p(n)$ is calculated in (3). Then *conf* is the maximum value of the minimum $h(S_i,S_j)$ of each pair S_i, S_j 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 $conf = \max\{\min(0.2,0.4), \min(0.2,0.8), \min(0.4, 0.8)\} = 0.4$. We do not choose *conf* to be $\min\{h(S_i)\}$, $i=1, \ldots, L$ since such decision is rather restrictive because when the reliability of a source at a n-level has the minimum value of those of all sources of m level with $m > n$ then, the entire confidence depends only on this source. The rule in (1), which concludes the n-level situational context p, takes into consideration the reliability of the sources, as defined in (4). The proposition "p_1 is $conf_1$" in (4) denotes the confidence on the observation or conclusion of the instance v_i of p_i. If $p_i \in \mathbf{P}(0)$ then, $conf_i$ is the reliability h_i of the source p_i. The confidence *conf* on the value v of p is calculated by (3) given that the confidence values $conf_i$, $i = 1, \ldots, L$, of the p_i antecedents of p have been calculated. The most probable situational context p along with the corresponding degree of confidence *conf* concluded by (4), refers to the *context fusion result*. The proposed model aims at evaluating how such conclusion holds true with respect to the degree of reliability on sensor readings, as discussed later.

$$conf = \max_{v=1..\binom{L}{2}} \left\{ \min_{(i,j)\in L\times L} \left(h(S_i), h(S_j)\right)_v \right\} \quad (3)$$

$$[(p_1 \text{ is } v_1) \wedge (p_1 \text{ is } conf_1)] \wedge \ldots \wedge [(p_k \text{ is } v_k) \wedge (p_k \text{ is } conf_k)] \rightarrow [(p \text{ is } v) \wedge (p \text{ is } conf)] \quad (4)$$

3. Probabilistic Context Fusion

We adopt the probabilistic fusion from [4], which is based on Dynamic Bayesian Networks (DBN) [5]. 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. The random variables of the DBN are (i) ground contextual attributes $p(0) \in \mathbf{P}(0)$ (i.e., sensor readings) and, (ii) situational context $p(k) \in \mathbf{P}(k)$ with $k \geq 1$. $p(k)$ at time t can affect (i) a situational context $p(m)$ with $m < k$ and (ii) an attribute $p(0)$ at the same time t (see Figure 1). For each sensor $S_i \in \mathbf{S}$ (or $p_i(0)$), $i = 0,\ldots, L$, we estimate the probability distribution $Prob(p_i(0)$ is $u_i \mid p_j(k)$ is $v_j)$, $p_j(k) \in \mathbf{P}(k)$, $k \geq 1$. Moreover, for every situational context without parent nodes, we determine the probability distribution $Prob(p_i(k)$ is $u_i \mid p_j(m)$ is $v_j)$, $i = 1,\ldots,d(p_j(m))$, with $p_i(k) \in \mathbf{P}(k)$, $p_j(k) \in \mathbf{P}(m)$, $k \geq 1$ and $m > k$.

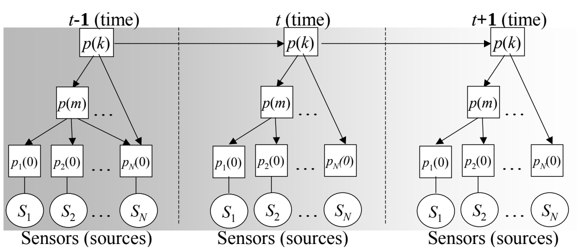

Figure. 1. A DBN represents the dependencies between random variables (situations / attributes) at different time slots.

3.1. Fusion Operator

The calculation of the conditional probability *Prob* of pieces of situational context determines accurately the value of the situational context at time t, i.e., $p = p(t)$, $p \in \mathbf{P}(k)$, defined in (5), where $p_i \in \mathbf{P}(i)$ with $i = 0,..k$-1. Equation (5) is the mathematical representation of the probabilistic fusion. It denotes the probability p having a value $v(t)$ at time t given the value $v(t$-1) of p at time t -1 and the values $v_i(t)$ of its dependable attributes at time t of lower levels. The probabilistic fusion result refers to the $p(t)$ that maximizes the joint probability, defined in (6). N_k in (6) is the number of pieces of situational context of k-level. Hence, $Prob(p(t))$ is the probability value of the occurrence of $p(t)$ situational context and we call such inference *probabilistic context fusion*.

$$Prob\left(p(t) \mid p(t-1), p_{k-1}(t), p_{k-2}(t), \ldots, p_0(t)\right) \quad (5)$$

$$p^*(t) = \arg\max_{i\in N_k}\left\{Prob\left(p_i(t) \mid p(t-1), p_{k-1}(t), p_{k-2}(t), \ldots, p_0(t)\right)\right\} \quad (6)$$

4. Reliability-based Probabilistic Context Fusion

Let $p = p(t)$ derive from the probabilistic fusion in (6). The probabilistic fusion determines p regardless of the reliability / confidence of the contributing sources. However, $Prob(p(t)) = Prob(p)$ at time t has to be estimated with a certain degree of confidence on sensor readings. Consider the fact that the fusion in (6) results to a high value of probability $Prob(p)$ but with a low confidence $conf_p$ on the sources. This could lead to a non-valid determination on the occurrence of p. Hence, $Prob(p)$ probability has to be re-evaluated taking into account the reliability on sensor readings. Such reasoning can be dealt with imprecise inference by characterizing the values of $Prob(p)$ and $conf_p$ with fuzzy sets (either type-1 or type-2 fuzzy sets). For that reason, the proposed model combines $Prob(p)$ and $conf_p$ in an approximate reasoning manner through fuzzy inference rules. The rule for inferring the k-level context is written in the *modus ponens rule* form illustrated in Figure 2. The observations v^*_i, $i = 1, \ldots, N$, are combined with the corresponding values of confidence $conf_i$. The concluded value v^* for p relates to the *possibility of occurrence* $Pos(p)$ (*confidence probability*) of p taking into account the joint probability $Prob(p)$ and the confidence value of each antecedent $conf_i$, $i = 1, \ldots, N$. $conf_i$ relates to fuzzy sets that describes the confidence on the v_i instance of p_i. The proposed inference in Figure 2 uses only one fuzzy controller at the highest level of conclusion. Specifically, the fuzzy fusion operator is unique at the highest k-level, which produces $v^*(k)$. For each level m, $m < k$, the confidence $conf_{p_i}$ on the values v_i are computed according to (3), where N_m is the number of attributes of the m-level rule, i =1, .., N_m, $p \in P(m)$. Hence, the fuzzy controller applies fuzzy inference at level k.

Three fuzzy sets $\mathbf{A}_l$ characterize the $Prob(p)$ for each probability value through a set of linguistic terms $l \in \{high, medium, low\}$ (see Figure 3). A *low* $Prob(p)$ denotes that the concluded context derives from a low probability of observation while, a *high* $Prob(p)$ denotes that a high value of confidence is assigned on the observation of p. A *medium* $Prob(p)$ denotes that one is not sufficiently certain or uncertain about the observation of p. Similarly, two fuzzy sets $\mathbf{C}_l$ characterize the confidence values $conf_p$ through a set of linguistic terms $l \in \{high, low\}$ (see Figure 3). A *low* $conf_p$ denotes that the concluded p is computed with a low degree of confidence i.e., low reliability on sensor readings. A *high* $conf_p$ indicates that, p derives from highly reliable sources. 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 x, y are fuzzy sets and $\vee$ is a triangular conjunctive norm (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 is applied over the $\mathbf{A}_l$ and $\mathbf{C}_l$ fuzzy sets resulting to the *possibilistic* value $y = Pos(p(t))$. F corresponds to three fuzzy sets $\mathbf{Y}_l$ describing a *low*, *medium* and *high* confidence probability $Pos(p(t))$, $l \in \{high, medium, low\}$ (see Figure 3). A fuzzy rule-base (see Figure 4) is constructed involving the $\mathbf{A}_l$, $\mathbf{C}_l$ and $\mathbf{Y}_l$ fuzzy sets with their corresponding linguistic terms for $Prob(p)$, $conf_p$ and $Pos(p(t))$. The appropriate fuzzy value of y is then represented by the fuzzy set $\mathbf{Y}(y)$ (see Table I(a)) depending on the input ($Prob(p)$, $conf_p$). Table I(b) depicts the concluded situational context based on the fuzzy inference of the confidence on sensor readings and the probabilistic fusion.

The fuzzy inference results to the fuzzy set $\mathbf{Y}(y)$, which is *defuzzified*, and then a crisp value of $Pos(p(t))$ is generated at time t. The fuzzy inference rules for reasoning about the probabilistic fusion and sources confidence are illustrated in Figure 4, including concentration (*very*) and dilution (*somewhat*) fuzzy set modifiers. We call such inference as *reliability-based probabilistic context fusion*, which corresponds to the enhancement of the probabilistic fusion for p produced by the equation in Table I(b). The fuzzy inference rules (see Figure 4) do not describe the situational context in which the probability and the confidence of the sources assumes simultaneously low values, i.e., such rule could be "*if* $Prob(p(t))$ is *low* and $conf_p$ is *low* then $Pos(p(t))$ is *high*". Instead, the confidence probability ($Pos(p)$) depends only on the value of the probability $Prob(p)$ (see the first rule in Figure 4). We exclude such rule from the proposed inference because another more improved reasoning formula has to be asserted (e.g., *modus tollens logic*[1]). Figure 5 depicts the behavior of the fuzzy inference rules. Evidently, when the degree of confidence assumes a zero value, which means that, the sensors readings are not reliable then, the confidence probability $Pos(p)$ assumes the value 0.5, given the highest probability $Prob(p)$. This implies that, the system is equally certain and uncertain when the fusion corresponds to an unreliable observation of context data. It should be noted that, the fuzzy sets can be either represented by human expert knowledge or derive from learning techniques, like *neuro-fuzzy* classifiers [6].

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

$\mathbf{Y}(y) = \bigvee_{1\le i\le m} [\mathbf{C}_{li}(Prob(p(t))) \wedge \mathbf{A}_{li}(conf_p) \wedge \mathbf{Y}_{li}(y)]$	(a)
$p^*(t) = arg\max_{i\in N_k}\{Pos(p_i(t))\} = arg\max_{i\in N_k}\{F(Prob(p_i(t)), conf_{p_i})\}$	(b)

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

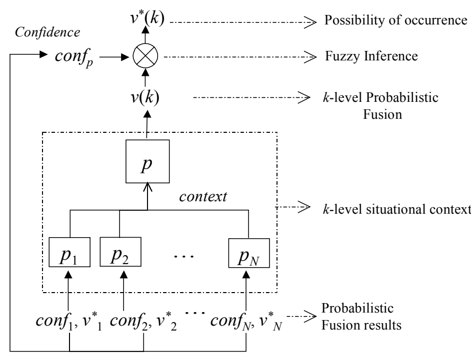

Figure. 2. Inference structure for reliability-based probabilistic context fusion.

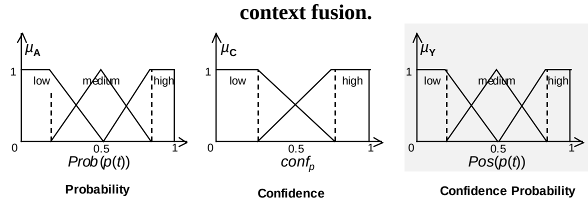

Figure. 3. Membership functions for the fuzzy sets of *Prob*(*p*(*t*)), *conf*$_p$ and confidence probability *Pos*(*p*(*t*)).

if $Prob(p(t))$ is *low* then $Pos(p(t))$ is *low*
if $Prob(p(t))$ is *medium* and $conf_p$ is *low* then $Pos(p(t))$ is very *low*
if $Prob(p(t))$ is *medium* and $conf_p$ is *high* then $Pos(p(t))$ is somewhat *high*
if $Prob(p(t))$ is *high* and $conf_p$ is *low* then $Pos(p(t))$ is *medium*
if $Prob(p(t))$ is *high* and $conf_p$ is *high* then $Pos(p(t))$ is *high*

Fig.4. Fuzzy Inference Rules

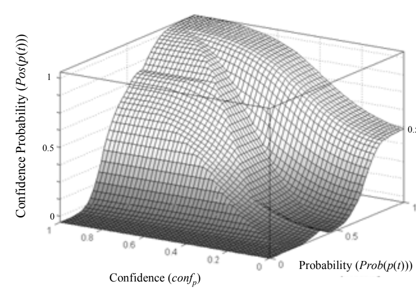

Figure. 5. Behavior of the fuzzy inference rules.

5. Experimental Evaluation

5.1. Experiment Setup

The evaluation of the reliability-based probabilistic fusion based on DBNs 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 situational context and location of the user are used interchangeably. The experimental setup was the 2-floor building of the Department of Informatics & Telecommunications (University of Athens, Greece). Each floor has dimensions of 30x100 meters and we used M = 35 symbolic locations (e.g., entrance, research room, corridors). The DBN that resulted under the previously described setup is an instance of the DBN depicted in Figure 1. 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 (RSS) measurements (Wireless LAN adapter). Context values (sensor readings) were recorded every second. The context p = *user is located in corridor* is formatted as follows: *AP1_RSS* is *–60 dBm* $\wedge$ *IRB1* is *visible* $\wedge$ *AP3_RSS* is *-30dBm*, where *AP1_RSS*, *IRB1* and *AP3_RSS* are attributes that conclude p.

5.2. Instantiating the Reliability of Sources

In order to quantify the reliability h_i for each sensor S_i, we used the probability distributions on diverse locations L for each sensor (see Table II) 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 were distributed equally between lower and highest value for a location L, the probabilities in the distribution (for that specific location) would be also equally distributed. The condition of equally distributed probabilities does not offer any *real* information from the sensor since every value v has approximately equal probability to appear. In order to obtain better results in location estimation, the samples should not be equally distributed. Let $V(L_i)$, $i = 1, \ldots, M$, be the discrete random variable which takes values from the column L_i of a probability distribution table (see Table II). M is the number of symbolic locations. Once the probability for a location L_i is equally distributed to all sensed values v_j, $j = 1, \ldots, k$, i.e., $V(L_i) = k^{-1}$ and k is the number of the sensed values, then, this means absolute ignorance on those sensed values. Hence, the higher the variance σ^2 of the random variable $V(L_i)$ the more information we obtain from a sensor for the specific location L_i (i.e., the sensor readings appear more reliable). The reliability h for a sensor is defined in (7) by calculating the mean value of all variances for each location. β in (7) 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.

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

Table II. Probability distribution for the sensor AP1

Value/Location		L_1	L_2		L_M
	v_1	0.5	0.0	…	0.1
	v_2	0.3	0.8	…	0.1
	…	…	…	…	…
	v_k	0.0	0.0	…	0.05

5.3. Reliability-based Fusion Evaluation

The experiments were performed for a week and at different hours of a day in order to have a clear image of the system's performance. The system computes the probabilities for each location and the estimated location of the user is the location with the maximum confidence probability, *Pos*(*p*(*t*)). Figure 6(a) illustrates the confidence probability for the fusion techniques: (i) probabilistic fusion using static Bayesian Networks (BN), (ii) probabilistic fusion using Dynamic Bayesian Networks (DBN) and (iii) reliability-based probabilistic fusion using DBN (RDBN). In the first case (static BN), we do not take into consideration the previous location of the user at time t –1 for the estimation of the current location at time t. The mean value of confidence probability is 73%. Through the use of DBN (second case), the mean value of probability increases to 85%. Finally, in the third case, where the reliability of sources is taken into account, the confidence probability reaches to 91%. Obviously, the confidence probability assumes better values, i.e., the system is sufficiently certain in order to infer context.

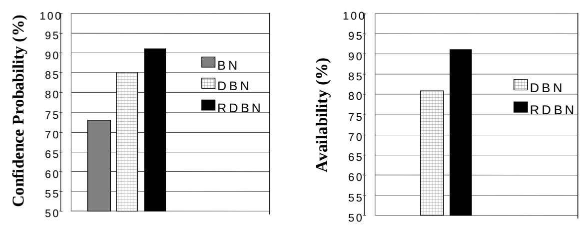

Figure. 6. (a) Mean confidence probability, (b) Availability of the system using (i) probabilistic fusion based (ii), reliability-based probabilistic fusion.

The fusion based on fuzzy inference assumes better performance when the probability value assumes values close to 0.5, i.e., the system is not sufficiently certain about the inferred context. Specifically, the degree confidence of sources supports the probabilistic fusion process to be either more certain about a situational context conclusion or more certain on the fact that the concluded context is not observed. This means that, the proposed context fusion uses fuzzy inference rules in the following deductive logic formula, that is, $p \rightarrow q$ and $\neg p \rightarrow \neg q$, where p and q is contextual attribute and situational context, respectively. Hence, if p is observed (probable) with a high value of confidence then, q is also observed with a high value confidence. On the other hand, if p is not observed (i.e., not probable and / or low confidence of sources) then, q is not sufficiently concluded. At this point, we quote the definitions of *accuracy* and *availability*, the most important features of a positioning system:

- *accuracy* denotes the distance within which the system has the ability to locate a user, e.g., 1-5 meters, and,

- *availability* denotes the percentage of time the system provides a specific *accuracy*, e.g., 80% of the time the system provides accuracy 1-5 meters.

The confidence probability about a location affects the availability of a positioning system. Figure 6(b) depicts the availability of the system for accuracy less the 5 meters using the techniques: (i) probabilistic fusion using DBN and, (ii) reliability-based probabilistic fusion using DBN. In the first case, the availability of the positioning system was 82 %. Conversely, the incorporation of the reliability *h* of sources (sensors) resulted to availability of 91 %. It is obvious that, the reliability of sources increases the certainty on the user position estimation, thus, improving the performance indicators of the positioning system.

6. Prior Work

The commercial system Ekahau [7] uses a calibration-based approach for location estimation thus, the location is calculated by means of Received Signal Strength measurements at the client side. The location estimation discussed in [4] based on DBN utilizes data from sensors of different technologies to infer user location. Moreover, context-awareness is not only location estimation and spatial awareness. By fusing contextual data other than location information is deemed appropriate for a context-aware application. The work in [8] deals with situational context recognition through data fusion techniques. In addition, fuzzy inference for situational context recognition is discussed in [9] but the sources reliability in the fusion process is not taken into account. Moreover, context estimation using Naïve-Bays classification is discussed in [10] without dealing with the imprecise nature of context. Finally, Location Stack [11] employs multiple sensor readings for location estimation.

7. Conclusions and Further work

In this paper, we present a model for context fusion, which exploits data from sensors or lower level context in order to estimate the current user context. We extended the work in [7], by taking into consideration the reliability of sources. Along with sensor data, the inferred context and the confidence of the sources are counted in the fusion process. Fuzzy inference rules are used in order to infer a more elaborated and holistic fusion result based on the probabilistic distribution of the situational context. The experimental evaluation of the proposed model proved its capability for context fusion. In addition, a method for calculating the degree of reliability of sources is introduced. According to such method, which is based on statistical quantities, we estimate the reliability of each sensor based on the *real* information that provides for every location.

Besides context representation, fusion, and inference, the need for adaptive intelligent applications is extremely important in a pervasive computing environment. Specification of temporal relationships between contextual attributes in context fusion is significant where applications and devices should be coordinated according to the current context of multiple users. A system that infers multiple simultaneous pieces of situational context from the fusion of diverse attributes is very important. Our research is based on the integration of additional information, e.g., sensor working time, to the estimation of the reliability of a sensor.

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