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A Lightweight Distributed Architecture to Integrate Fuzzy Relevant Objects in Real-Time Environments

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Abstract. The development of intelligent environments from scratch means an arduous and complex process. In these environments, the integration of sensors and the design of processing information in real time are key aspects in order to generate feasible solutions. To shed light on this context, in this contribution, we present an architecture for information processing based on object distribution services. The capture and processing of data are developed ubiquitously within mobile devices and ambient computers by means of peer to peer based on fuzzy temporal subscriptions. The main advantage of the use of fuzzy temporal subscriptions is that the information is received by a subscriber when it reaches a desired level of relevance for this subscriber, implying a decrease in the communication burden in the architecture. In order to illustrate the usefulness and effectiveness of our proposal, a scene of an user performing an activity in an intelligent environment is described by means of his interactions with the environmental objects and the identification of users by marker-based tracking.

Keywords: Intelligent environments · Ambient middleware · Object distribution services · Real-time processing · Marker-based tracking

1 Introduction

Internet of Things (IoT) [23] is emerging as a new paradigm where Ambient Intelligence [30] and Ubiquitous Computing [29] converge [21]. These paradigms locate the information processing in the everyday objects properly, but there are new challenges which arise in order to develop collective intelligence in these frameworks.

In this context, there are two key issues that should be addressed. On the one hand, the integration of the heterogeneous data and, on the other hand, the information processing.

The first issue is the integration of data from heterogeneous sources, which is critical to provide an affluent ambient layer. There is a wide range of sensors that can be deployed in an intelligent environment that collect multiple data,

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such as, mobile, wearables, ambient devices. The mobile devices integrate movement, location and connectivity by means of sensors and wide-range protocols (accelerometer, GPS, NFC, Wi-Fi, etc.). Meanwhile, ambient devices are collecting information from our environment using low-power protocols (Z-Wave or ZigBee) in light sensors, or WLAN protocols in vision or audio sensors.

In summary, each sensor can send and receive the data from the sensor network in the lowest level of the communication layer providing physical interaction with the hardware. To do so, there are different languages or platforms in the sensor network such as C++, Android, Objective-C, Java or Ruby. Because of this, the mosaic of devices, languages and protocols needs for be accessible homogeneously to develop real scenes with heterogeneous sensors.

The second issue is the information processing that requires structural data and procedures to generate new information from low-layer information [10]. In the literature, several approaches have been proposed to manage these issues, in which the efforts have been focused on providing general and ad hoc models. With respect to the standard structural models, it is noteworthy SensorML [2], developed by Open Geospatial Consortium which includes geolocation or discovering in a XML schema. Concerning the semantic annotating for sensors, it is relevant the W3C Semantic Sensor Networks (SSN) specifications [4,8]. Regarding ad hoc models, there are approaches which provide own models which fit better within ad hoc reasoning processes or streaming requirements [3,7,24,25].

Furthermore, a key aspect in the second issue is the middleware infrastructure in which input/output data are connected by remote services in distributed environments. The adequate distribution of services in ambient environments is vital to provide sensitivity to real time [1] for distributing the information processing in several central processing units [17,27]. There are several relevant open middlewares that provide sturdy solutions in ubiquitous and ambient contexts. Among them, it is noteworthy ZeroC Ice [11,28] that is an object-oriented distributed computing tool with support for several languages and platforms as well as Global Sensor Network (GSN) that applies sliding window management [26] in changing data stream [14]. Finally, OpenIot increases the characteristics of GSN adding top-k subscriptions over sliding windows (top-k/w subscriptions) [20] and semantic open-linked data techniques. The subscription process has been demonstrated to be adequate for IoT, highlighting the implementation of Data Distribution Service for Real-Time Systems (DDS) by Object Management Group (OMG)[1].

The aim of this contribution is to provide a straightforward architecture to process heterogeneous information from real-time in intelligent environments. This architecture is based on a peer-to-peer communication in which fuzzy relevant objects are distributed in subscriptions in a sliding window in time.

To do so, the contribution is structured as follows: the use of appropriate techniques in our proposal is discussed in Sect. 2 and the proposed architecture is described in Sect. 3. In Sect. 4, a scene developed under the proposed architecture

[1] http://www.omg.org/spec/DDS/1.2/.

using video processing as well as ambient and mobile sensors is described. Finally, in Sect. 5, conclusions and future works are pointed out.

2 Requirements and Cost-Value Approach

This contribution is focused on the development of an straightforward architecture in which heterogeneous information provided by a sensor network is spread in real time.

To do so, it is necessary to process the information provided by mobile, ambient and vision sensors. Some previous solutions deal with data using heavy computing techniques in desktop computers, delegating light devices to wrappers of raw data. For example, GSN needs for MySQL to manage and store the data streams or OpenIot provides subscription services just in server side. Moreover, there are some problems to integrate GSN in light devices within other platforms or languages [9].

In this contribution, a minimum scalable architecture is proposed in which each sensor (mobiles, ambient and vision) sends stream of processed data to subscribers in a dynamic way. Furthermore, each sensor transmits its streams in real time to top-k/w subscriptions [20] under a fuzzy [31] approach based on the relevant information for each subscription. The main advantage of this fact is that the centralization is not necessary, providing a peer-to-peer communication where the most relevant fuzzy objects are distributed in a sliding window in time.

Furthermore, due to the fact that each sensor depends on each manufacturer platform, a metalanguage middleware is required in order to deploy the subscription services. In this contribution, ZeroC Ice is chosen as middleware because it supports transparent communication for several languages (C++, .NET, Java, Python, Objective-C, Ruby, PHP, and JavaScript) and protocols (TCP, UPD and SSL).

Finally, regarding data representation, a fuzzy Entity-Attribute-Value (EAV) model [22] is proposed in order to describe objects from the ambient environment. This basic similar description for semantic representation is used in OpenIot by means of Resource Description Framework and the Linked Sensor Middleware [15]. As is detailed in next sections, the entity-attribute-value model is suitable to decompose the objects in distributed nodes and to integrate them in real time.

3 Architecture for Distributed Fuzzy EAVs in *alpha*/w Subscriptions

In this section, the proposed architecture for streaming fuzzy objects under the subscription paradigm with relevant information is described. Figure 1 illustrates the processing and flow of information from devices to subscribers under our approach that are described in detail in the following subsections. To do so, first, the meta model based on a fuzzy representation of EAVs is presented for

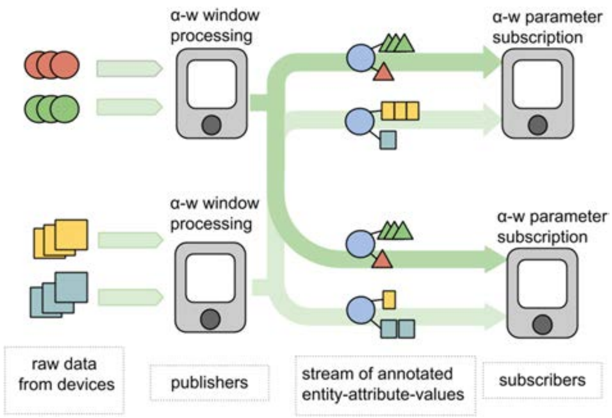

Fig. 1. Flow of information from devices to subscribers

defining the relevance of each data source. Then, the relevant information to be transmitted is defined by Top-α/w distributed publishers/subscriber. Finally, the dynamic nature of the architecture is addressed.

3.1 Metadata Model: Fuzzy Temporal EAV

In this section, the fuzzy version of EAV to handle imprecise environmental object representations in our proposal is described.

Fuzzy entities, attributes and values has been used satisfactorily in many real-world applications due to information is often vague or ambiguous [18], providing the following advantages: (i) *flexibility* to represent concepts, physical or virtual objects, (ii) *data processing independence* and (iii) *interoperability* to be analyzed and processed by computers or humans.

The proposed environmental model is defined as a set of fuzzy temporal entities within a set of attributes wit a set of fuzzy temporal values. This representation comes from a generalization of an ad hoc structure [3].

The temporal dimension of the data from mobile, ambient and vision source has been defined by a time-stamp that inserts the reading or changing data in milliseconds in the Unix time format. This stamp is used from sliding window to stream the most recent data at an interval in time.

The relevance of data has been defined by a fuzzy value between [0,1] [31] that is estimated by the publisher. Therefore, each node that generates and streams the data must define how relevant are the data, based on the context of the measure. For example, it can represent the probability, uncertainty or importance, enabling subscribers to apply an alpha-cut [31] to receive only relevant data.

So, each fuzzy temporal EAV in our proposal is defined by the following elements:

- *Id.* An universal identifier of the object.
- *Type.* A type description of the entity (e.g. Person, Mobile, Ambient Device).
- *Relevance.* A fuzzy relevance value between [0,1].
- *Stamp.* A time stamp from the last modification in milliseconds.
- *Attributes.* A set of attributes that characterized the object in which each attribute is defined by
  - *Id.* An universal identifier of the attribute.
  - *Type.* A type description of the attribute (e.g. Location, Movement, Open).
  - *Values.* A set of values where each value is defined by
    - *Type.* The nature of the value (e.g. Integer, Double, String, Float, Location2D, Location3D).
    - *Relevance.* A fuzzy relevance value between [0,1].
    - *Stamp.* A time stamp from the last modification in milliseconds.

3.2 Top-α/w Distributed Publishers/subscribers

Our approach in based on a peer to peer communication based on fuzzy temporal subscriptions to transmit preprocessed information, which is relevant to the subscriber, offering a distributed ubiquitous (mobile, ambient or desktop) sensor network.

This approach provides several advantages:

- The information processing is distributed in several central processing units.
- The subscribers can define (as far as possible) the time and relevant data for notification.
- The subscribers obtain processed instead of raw data facilitating the handle of their own information management.

In order to define the relevant data, each subscriber can define temporal constrains and a fuzzy threshold of relevance:

- TNotification. The minimal time that the publish must wait to notify to the subscriber.
- TWindow. The temporal window of relevant data to be summarized. This is, the set of values where $t - stamp < TWindow$, where t is current time.
- Alpha-Cut. The minimal alpha value of relevance that entities and values must overcome. The publisher apply this alpha-cut filtering the objects where $relevance > \alpha$.
- Aggregation operator $\cup$. Based on the nature of data, subscribers can specify optionally an operator to summarize the data, for example: min, max or average. If there not exists any operator, all samples where $relevance > \alpha$ in the temporal window are sent.

In the publisher side, the devices receive the data from their sensors, storing them in a temporal window. When the notification time interval of each subscriber expires, they send the relevant data applying the fuzzy temporal filtering, see Fig. 1. In this approach, the crisp definition of the temporal component is required to avoid the possible duplication of data in consecutive intervals due to vague or imprecise temporal windows.

4 Description of a Real Scene Based on Fuzzy EAVs in *alpha*/w Subscription

In this section, a description of a real scene in an intelligent environment is presented, which is modeled and processed under our proposed architecture. The presented scene show an a user makes a tea in an intelligent environment, specifically in a kitchen. First of all, the user goes into the kitchen and takes a cup from the cupboard. Then, he fills the cup of water and heats it in the microwave. Finally, he drinks the tea and goes out of the room.

In the following subsection, the sensor network of the intelligent environment is described in which the scene has been carried out and, then, the real-time publishers/subscribers are indicated.

4.1 Sensor Network of the Intelligent Environment

The sensor network in the kitchen integrates several sensors that provided heterogeneous data:

- Mobile devices that provide information of the scene in terms of accelerometer and touching tags (NFC).
- Ambient sensors based on switch that are located at the doors that separates the areas of the smart environment, the doors of some home appliances (microwave, fridge, etc.) as well as at the doors of kitchen furniture.
- Vision sensor and vision marks. The vision sensor corresponds with an IP camera that records the images from the scene and provide the location and identification using vision marks located in a T-shirt with four vision markers, see Fig. 2.

It is noteworthy that in this scene a T-shirt has been worn by the user that includes four id markers (two larger in frontal and back side and two smaller

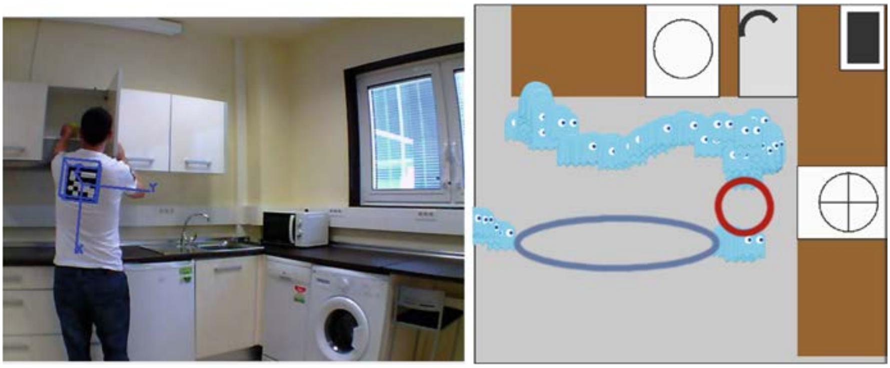

Fig. 2. (A) A frame and mark detection from scene (B) Projection of 3D positions from tracker publisher in room map.

in sleeves) in order to identify the user and his location by using an open source project: Minimal library for Augmented Reality applications (Aruco) [6] to detect markers.

So, candidate markers are detected, obtaining the identifiers and calculates the rotation and translation transformation matrix (R,S). Moreover, providing the real size of markers, the model view projection matrix (H) is obtained to estimate a 3D position from marker view to 3D position from the camera view. Finally, a naive modification has been integrated to provide the dynamic size of marker based on its identifier.

4.2 Real-Time Publishers/Subscribers

One of the main advantages of our proposal is that data processing is distributed. In the proposed scene, the following nodes have been deployed:

– *A mobile publisher.* This node is a multi-sensor source that streams motion from an accelerometer and reading events from NFC tags using a top-α/w processing. On the accelerometer signal, a single raw value of motion has been calculated as the square root of the sum of the squares of the components X, Y and Z $motion = \sqrt{x^2 + y^2 + z^2}$. Besides, it is included a fuzzification process to estimate the *relevance* of the fuzzy object based on the motion value using a membership function of a fuzzy set which represents the concept of *being in movement*. The membership degree is calculated by a linear increasing membership function $I[a, b]$, where lower or equal values to a are 0, greater or equal to b are 1, and a linear function that changes smoothly from 0 to 1 in a straight line in values between a and b. In this case, the domain values from the mobile accelerometer are in range $[0, 2]\,\mathrm{m/s}^2$ and we have defined a linear increasing function $I[0, 0.5]$ that calculates the relevance of motion values from mobile sensor in range $[0, 1]$.
  The semantic of the tags in the scene simulates the automatic opening door of the kitchen using a NFC tag. In Fig. 3, we show the events received (in red dots) when the user enters and leaves the room. Any fuzzification has been associated to NFC events where relevance has been evaluated as 1 (crisp value).
  In addition, using the Google Account Id from the mobile, we can identify the user and generate an ad hoc fuzzy EAV for each mobile. An example of stream data from mobile publisher is: $\{id$: "$PerryMason$", $stamp$: $1432207248128\}$, $attributes$: ["$Movement$" : $\{value$: 7.3, $relevance$: 0.9, $stamp$: $1432207248118\}$, "Tag" : $\{value$: "$touchoven$", $relevance$: 1.0, $stamp$: $1432207248081\}$].
– *An ambient publisher.* This node streams open/closed events from ambient sensor based on switch using a top-α/w processing.
  The open/close sensor returns asynchronously two trigger: a change of state and low-battery state. We include a fuzzification process to estimate the *relevance* of the fuzzy objects from the change of state based on the low-battery messages. When a low-battery state is included in the measure, we set

$relevance = 0.5$. Otherwise, $relevance = 1.0$. In addition, using the id from each ambient sensor, we can generate an ad hoc fuzzy EAV for each measure. An example of stream data from ambient publisher is:$\{id : \text{“}Oven\text{”}, stamp : 1432207248128\}, attributes : [\text{“}Open\text{”} : \{value : true, relevance : 0.5, stamp : 1432207248118\}]$.
In Fig. 3 are shown the events received in the scene from a subscriber. These are, three events (in green dots) when the user opens the cupboard and when he opens the microwave.

– *An tracker publisher.* This node streams location and identification events from users using a top-α/w processing.
The 3D location and the user identification has been integrated in a stream publisher within Aruco detection. A temporal fuzzification has been associated to 3D positions where relevance has been evaluated using linear increasing membership function $I[TWindow, 0]$ that prioritizes the most recent data in the interval $[t_0 - TWindow, t_0]$ using the difference between the current time t_0 and the time of the mark detection $stamp$. This semantic represents An example of stream data is: $\{id : \text{“}PerryMason\text{”}, stamp : 1432207248128\}, attributes : [\text{“}Location3D\text{”} : \{value : XYZ(4.25, 2.70, 1.23), relevance : 0.8, stamp : 1432207248118\}]$.

In Fig. 2 the 3D transformations from the real scene into a sketch map are depicted. Table 1 shows the performance of vision markers to identify and track the user. The detection percentage in the scene is significant (closer to 40 %), providing a smooth tracking. The average of distance to consecutive marker detection is 2,67, this is, the number of frames between a marker detection and the next. However, there is a lack of information in non frontal poses, as the value of maximal distance to consecutive marker detection determines. It is shown in Fig. 2: with red ellipse, the lack of markers when the T-shirt is distorted by drinking cup movements; with blue ellipse, the undetected cornered frames when user leaves the room. At the end of this movements, the sleeve markers,

Table 1. Statistical data from marker detection

Number of frames	583
Number of marker detections (ms)	219
Percentage of marker detection	37,57 %
Average time of marker detection	55,47 ms
Number of frontal and back marker detections	212
Number of sleeve marker detections	7
Average of distance to consecutive marker detection	2,67
Standard deviation of distance to consecutive marker detection	10,86
Max of distance to consecutive marker detection	131

Table 2. Data stream reduction from accelerometer in mobile device

Number of samples from accelerometer (ns) in mobile device	873
Samples from accelerometer per second	19,41
Number of aggregated samples from accelerometer in $TNotification = 1000\,\text{ms}$	43
Number of accelerometer events from subscriptions (αs) $TNotification = 1000\,\text{ms}$, $TWindow = 1000\,\text{ms}$, $\alpha = 0.15$ and $\cup = MAX$	32
Ratio of reduction (ns/αs)	27,28

Table 3. Data stream reduction from vision sensor

Number of marker detections (ms)	219
Number of events from vision sensor from subscriptions (αs) with $TNotification = 1000\,\text{ms}$, $TWindow = 1000\,\text{ms}$, $\alpha = 0.15$ and $\cup = MAX$	17
Ratio of reduction (ms/αs)	12,89

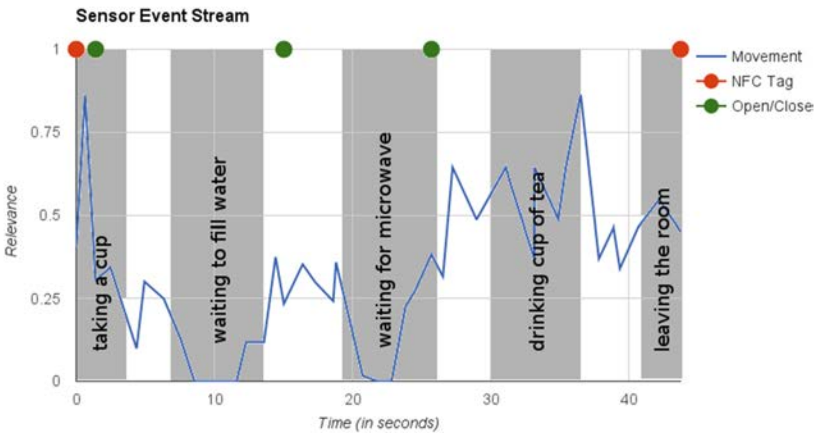

Fig. 3. Stream events from mobile and ambient publishers. $\alpha = 0.15, TWindow = 1000\,\text{ms}, TNotification = 1000\,\text{ms}$. Accelerometer aggregator $\cup = MAX$. None ambient and NFC aggregator (Color figure online).

however they are not numerous, provide a vital information to track the user when goes out of the room.

On the other hand, the data stream reduction from accelerometer and vision sensor, which generate both high-frequency data, with $TNotification = 1000\,\text{ms}$ and $\alpha = 0.15$ subscriptions are shown in Tables 2 and 3. We highlight the significant ratio reduction from number of raw data to events from subscription.

The collected data from the scene are accessible in the URL[2].

[2] http://ceatic.ujaen.es/smartlab/ucami_smartlab_scene.zip.

5 Conclusions and Future Works

In this contribution a lightweight distributed architecture for intelligence environments in real time has been presented. We have evaluated previous open approaches focusing on the information processing in centralized computers, such as GNS or OpenIot.

For this reason, interesting topics included in GSN or OpenIot has been translated to our solution using an open multi platform middleware (ZeroC Ice). We have proposed an architecture based on top-k/w subscription, which restricts information processing to a certain window of relevant elements recently observed on the stream, which we call as α/w subscription. So, we have proposed a fuzzy processing of objects conducted in light devices where each subscriber can defined a alpha-cut of relevance. Other parameters to enrich the information processing to the context of the user, such as parametrizing membership function [16], are going to be considered in future works.

Concerning the data representation model, we have defined a distributed fuzzy entity-attribute-value scheme integrated in the middleware. Related works use similar models, such as Tuple Space, in mobile middlewares due to their simplicity, flexibility, performance and scalability [5,19].

In the design of the architecture, we have defined a publisher/subscriber model that is dynamically linked by machine-to-machine communications. This paradigm increases the composition of interactive capabilities in the IoT [13]. In results, we have developed a real scene where three distributed nodes publish data from mobile devices, ambient sensors and video processing in real time. The scene integrates a video processing based on vision marker tracking in order to capture the identification and the location of the users. The results show an encouraging performance.

In future works, we aim to use these id vision marks in vision sensor with camera auto-calibration, where static marks located in walls determine the absolute location of users. In addition, it will be useful in multi-occupancy, identifying the activities of several users in the same space and associating activities based on multi sensors events.

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References

1. Balan, R.K., Satyanarayanan, M., Park, S.Y., Okoshi, T.: Tactics-based remote execution for mobile computing. In: Proceedings of the 1st International Conference on Mobile Systems, Applications and Services, pp. 273–286. ACM, May 2003
2. Botts, M., Robin, A.: OpenGIS sensor model language (SensorML) implementation specification. OpenGIS Implementation Specification OGC, 07–000 (2007)
3. Castro, J.L., Delgado, M., Medina, J., Ruiz-Lozano, M.D.: Intelligent surveillance system with integration of heterogeneous information for intrusion detection. Expert Syst. Appl. **38**(9), 11182–11192 (2011)

4. Compton, M., Barnaghi, P., Bermudez, L., Garcia-Castro, R., Corcho, O., Cox, S., Taylor, K.: The SSN ontology of the W3C semantic sensor network incubator group. Web Semant. Sci. Serv. Agents. World Wide Web **17**, 25–32 (2012)
5. De, S., Nandi, S., Goswami, D.: Tuple space enhancements for mobile middleware. Int. J. Commun. Netw. Distrib. Syst. **12**(3), 299–326 (2014)
6. Garrido-Jurado, S., Muñoz-Salinas, R., Madrid-Cuevas, F.J., Marín-Jiménez, M.J.: Automatic generation and detection of highly reliable fiducial markers under occlusion. Pattern Recogn. **47**(6), 2280–2292 (2014)
7. Gomez-Romero, J., Patricio, M.A., García, J., Molina, J.M.: Ontology-based context representation and reasoning for object tracking and scene interpretation in video. Expert Syst. Appl. **38**(6), 7494–7510 (2011)
8. Neuhaus, H., Compton, M.: The semantic sensor network ontology. In: AGILE Workshop on Challenges in Geospatial Data Harmonisation, Hannover, Germany, pp. 1–33 (2009)
9. Perera, C., Zaslavsky, A., Christen, P., Salehi, A., Georgakopoulos, D.: Connecting mobile things to global sensor network middleware using system-generated wrappers. In: Proceedings of the Eleventh ACM International Workshop on Data Engineering for Wireless and Mobile Access, pp. 23–30. ACM, May 2012
10. Haefner, K.: Evolution of Information Processing Systems: An Interdisciplinary Approach for a New Understanding of Nature and Society. Springer, Heidelberg (2011)
11. Henning, M.: A new approach to object-oriented middleware. IEEE Internet Comput. **8**(1), 66–75 (2004)
12. Henning, M., Spruiell, M.: Choosing middleware: why performance and scalability do (and do not) matter, 1 September 2009. http://www.zeroc.com/articles/IcePerformanceWhitePaper.pdf
13. Kortuem, G., Kawsar, F., Fitton, D., Sundramoorthy, V.: Smart objects as building blocks for the internet of things. IEEE Internet Comput. **14**(1), 44–51 (2010)
14. Kifer, D., Ben-David, S., Gehrke, J.: Detecting change in data streams. In: Proceedings of the Thirtieth international conference on Very Large Data Bases (VLDB Endowment), vol. 30, pp. 180–191, August 2004
15. Le-Phuoc, D., Nguyen-Mau, H.Q., Parreira, J.X., Hauswirth, M.: A middleware framework for scalable management of linked streams. Web Semant. Sci. Serv. Agents. World Wide Web **16**, 42–51 (2012)
16. Liu, H., Jacobsen, H.A.: A-ToPSS: a publish/subscribe system supporting imperfect information processing. Proceedings of the Thirtieth International Conference on Very large Data Bases (VLDB Endowment), vol. 30, pp. 1281–1284, August 2004
17. Liu, G.: Distributing network services and resources in a mobile communications network. US Patent No. 5,825,759. US Patent and Trademark Office, Washington, DC (1998)
18. Ma, Z.: Fuzzy Database Modeling of Imprecise and Uncertain Engineering Information. Springer, Heidelberg (2006)
19. Picco, G.P., Balzarotti, D., Costa, P.: Lights: a lightweight, customizable tuple space supporting context-aware applications. In Proceedings of the 2005 ACM Symposium on Applied Computing, pp. 413–419. ACM, March 2005
20. Pripužić, K., Žarko, I.P., Aberer, K.: Top-k/w publish/subscribe: a publish/subscribe model for continuous top-k processing over data streams. Inf. Syst. **39**, 256–276 (2014)

21. Marie, Pierrick, Desprats, Thierry, Chabridon, Sophie, Sibilla, Michelle: Extending Ambient Intelligence to the Internet of Things: New Challenges for QoC Management. In: Hervás, Ramón, Lee, Sungyoung, Nugent, Chris, Bravo, José (eds.) UCAmI 2014. LNCS, vol. 8867, pp. 224–231. Springer, Heidelberg (2014)
22. Nadkarni, P.: The EAV/CR model of data representation. Technical report, Center for Medical Informatics, Yale University School of Medicine (2000)
23. Kopetz, H.: Internet of things. In: Kopetz, H. (ed.) Real-Time Systems, pp. 307–323. Springer, New York (2011)
24. Rodríguez, N.D., Cuéllar, M.P., Lilius, J., Calvo-Flores, M.D.: A fuzzy ontology for semantic modelling and recognition of human behaviour. Knowl.-Based Syst. **66**, 46–60 (2014)
25. Roggen, D., Lukowicz, P., Ferscha, A., Millán, J.D.R., Tröster, G., Chavarriaga, R.: Opportunistic human activity and context recognition. Computer 46, 36–45 (2013). IEEE Computer Society (EPFL-ARTICLE-182084)
26. Salehi, A.: Design and implementation of an efficient data stream processing system. Doctoral dissertation, École Polytechnique Féd'erale de Lausanne (2010)
27. Verissimo, P., Rodrigues, L.: Distributed Systems for System Architects, vol. 1. Springer Science & Business Media, New York (2012)
28. Villanueva, F.J., Villa, D., Moya, F., Barba, J., Rincón, F., Lopez, J.C.: Leightweight middleware for seamless HW-SW interoperability, with application to wireless sensor networks. In: Design, Automation & Test in Europe Conference & Exhibition (DATE 2007), pp. 1–6. IEEE, April 2007
29. Weiser, M.: The computer for the 21st century. Sci. Am. **265**(3), 94–104 (1991)
30. Zelkha, E., Epstein, B., Birrell, S., Dodsworth, C.: From devices to ambient intelligence. In: Digital Living Room Conference, vol. 6, June 1998
31. Zadeh, L.A.: Fuzzy sets. Inf. control **8**(3), 338–353 (1965)