User Presence Detection Based on Tracking Network Activity in SmartRoom

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***Abstract*—The SmartRoom system provides a set of services for assisting collaborative activity when many participants are physically present in the same room. The SmartRoom service intelligence is due to the use of diverse sources of information on ongoing activity. One promising source is information on user presence and network activity of the participants. In this paper, we consider the problem of utilizing such an information source for smart spaces based on the Smart-M3 platform. We employ the Innorange technology, which is one of the many examples for passive radio detection in WLAN. We define scenarios with this information source for use in SmartRoom services. We propose an integration solution oriented to Smart-M3 applications. Our software prototype is integrated into the SmartRoom system. Experimental study confirms the feasibility and reasonable performance of the proposed solution.**

I. INTRODUCTION

The SmartRoom system provides a set of digital information services for assisting such collaborative activity as conferences, meetings, and lectures [1], [2], [3]. Activity is spatially localized in a physical room, although remote participation is also possible. Digital equipment of the room consists of devices with sensing, processing, network, and user interfacing capabilities. A device hosts one or more agents that sense or generate, process and share knowledge of the collaborative activity.

Smart spaces provide an environment for heterogeneous devices and programmable software agents to share their resources and services [4], [5]. Smart-M3 is an open-source interoperability platform for information sharing [6]. Smart-M3 provides its applications and their services with a common "smart space" to share dynamic knowledge and to make reasoning cooperatively. It allows implementing information service-oriented systems as multi-agent knowledge-driven activity in a computing environment [7], [8], [9], [10]. A Smart-M3 semantic information broker (SIB) maintains a smart space, representing its informational content in RDF triples, thus applying technologies from the Semantic Web. A Smart-M3 application consists of knowledge processors (KPs) that share information and form the smart space. Each KP publishes information for shared use and makes its semantic relation. A service is a result of cooperation of several KPs.

Based on the Smart-M3 platform, the SmartRoom system creates a domain-specific knowledge sharing environment. Human participants become SmartRoom users that participate in the ongoing activity by accessing and using services via their personal mobile devices (e.g., smartphones). The corresponding KPs are personal SmartRoom clients, see their development status in [11], [13], [12], [14]. Each SmartRoom user can browse informational content shared by prospected speakers.

We continue our ongoing development of Smart-M3 oriented mechanisms for user presence detection and their use for SmartRoom services [15], [16]. The intelligence of SmartRoom services and their delivery can be further extended by utilization of runtime information on user presence in the room, including physical and virtual presence. This information is associated with network activity of personal mobile devices. Well-known methods of passive radio detection can be applied to measure received signal strength indication (RSSI) for each device during the ongoing collaborative activity. In this paper, we consider how to organize collection of such information and how to use the information in SmartRoom services. As a reference technology, we apply the Innorange footfall technology (http://www.innorange.fi/), which is one of many available now on the market. We expect that selection of another technology would lead to similar results.

The rest of the paper is organized as follows. Section II describes related work. Section III introduces usage scenarios that show how SmartRoom services can benefit from information on user presence and network activity. Section IV describes ontological representation for this type of information and considers architectural scheme for integrating the additional information source to the SmartRoom system. Section V considers our model that describes the user presence state in runtime. Section VI studies the possibilities and limitations of the proposed solution. Section VII concludes the paper.

II. RELATED WORK

There exists a lot of work on methods, models and algorithms for passive radio detection based on the RSSI approach. Recently, Narzullaev and Park [17] proposed a locating algorithm that combines the calibration procedure with the

RSSI fingerprint prediction model. It requires only a few RSSI samples, thus significantly reducing the calibration time. The rest of the RSSI database is then estimated from an accurate RSSI prediction algorithm.

Ng *et al.* [18] presented an indoor location tracking system. Several re-program access points for wireless communication are placed in a room to form a wireless network. RSSI readings are collected and analyzed to detect indoor locations of mobile users.

Nuzzer [19] is a device-free passive localization system for tracking mobile entities in a large indoor environment. Probabilistic techniques for localization of a single entity are applied. An algorithm is proposed for estimating the number of entities in the area of interest and localizing them into coarse-grained zones.

The above work is oriented to indoor environments within large buildings. The solutions are of high cost and complexity since they require essential equipmen, e.g., additional re-program access points and a lot of measurements to process. In the case of SmartRoom, collaborative activity is localized in a relatively small room. There is no requirement of very high accuracy precision, which needs resource-expensive processing. Lightweight and low-cost solutions are preferable for this case.

Such a solution can employ the Innorange footfall technology, which we preliminary studied in SmartRoom settings [15], [16]. The technology can be used as a reference case, allowing replacing with a similar RSSI-based technology for passive radio detection for given MAC addresses of participating mobile devices. In this paper, we propose a full-valued integration solution, which can augment a Smart-M3 application with the information source on user presence and network activity. Our implementation and validation study are particularized for the needs of SmartRoom system.

III. Usage Scenarios

Let us first describe the idea of methods for passive radio detection. They are based on RSSI measurements associated with a given mobile device. If the device belongs to a concrete person then the measurements provide information on user presence. In the SmartRoom case, personal mobile devices operate in WLAN and users access services from the devices. A mobile device transmits data by radio signals, each has such a characteristic as RSSI. Any RSSI value reflects the distance between the signal source and the receiver. The accuracy is sensitive to presence of obstructions and reflective surfaces.

In particular, such passive radio detection is implemented in the Innorange footfall technology. It is possible to discover how people are moving between the service points, from where they are coming, and where they are going to. The Innorange technology is built in a dedicated Wi-Fi presence sensor (e.g., TP-Link WDR3600). Its custom OpenWRT-based software module continuously analyzes MAC addresses of mobile devices operating in WLAN. When a device generates network traffic to the WLAN, every traffic unit has received a RSSI value, timestamp and MAC address at the presence sensor. The closer the device is to the presence sensor the higher the RSSI value.

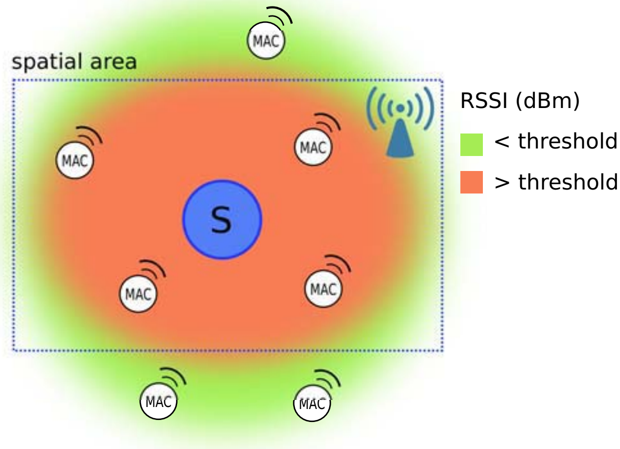

Fig. 1. Schematic view on spatial RSSI-based coverage

An Innorange Footfall sensor is mounted preferably near the center of the room to achieve the maximum possible coverage of the room spatial area. After the installation the calibration is needed for accurate evaluation of the WLAN RSSI threshold. If the RSSI value exceeds the threshold the device is treated as present in the room, see Fig. 1. Devices located outside will be behind obstacles and having the RSSI value is significantly less than devices in the room, so ensure the correct response of the presence sensor to such situations.

For the practical use, one needs to implement collection of RSSI measurements from the presence sensor and "MAC $\leftrightarrow$ user" mapping over the collected data.

Now let us consider scenarios for use of this type of presence detection in SmartRoom settings. Each scenario supports a set of services; we classify them into the following three groups.

S_1: *User arrival to the room.* Before starting the main activity, the users arrive and gather in the room (first-time join) and preparing/waiting the forthcoming activity. Detection of user arrivals activates personalized welcome services and provides runtime initialization for starting the main activity. For example, everyone can see who is ready to make presentations.

S_2: *User joins and leaves during the main activity.* Real-time status of every user provides important information for the activity agenda. For example, the system moves or cancels a planned presentation if its speaker is absent, or the system notifies the speaker that her/his talk is expected to start soon.

S_3: *Activity statistics.* During the main activity, personalized information is accumulated from the presence sensor. The information contains a timestamp, value of RSSI and MAC address. A record is stored for every traffic unit received by the presence sensor. At the end of the main activity a report is generated, which contains the overall level of network activity and the activity rate. Based on the level of network activity the system evaluates resources that each participant has contributed to the activity, e.g., the rate the user leaves the ongoing activity.

IV. USE IN SMART-M3 APPLICATIONS: ONTOLOGY AND ARCHITECTURE

Let us consider ontological representation of information collected from the RSSI measurements. Although we consider the case of SmartRoom, the representation can be adapted for use in other Smart-M3 applications.

The SmartRoom ontology describes the shared information (smart space content), including context of each user and service [3]. User context describes the recent user state and the services she/he accesses currently. Similarly, each service has its own unique context, which describes how the service is used and by whom. The context is shared in the smart space and is open to other KPs and their services.

Figure 2 shows our base ontology to represent information on user presence and to relate this information with other content. The ontology becomes a part of the SmartRoom ontology. User presence is based on the context of the user profile. The ontology of user profile contains his/her personal information, including the MAC-address of personal mobile device, as well as a variety of context information for services. When the user mobile device is detected by the sensor (Innorange), the presence service finds a matching profile and adds information on user presence (e.g., time of enter and last seen). The presence service tracks and modifies information on the user presence level and periodically updates the network activity metrics, including activity level, activity rate, and average RSSI value.

Each SmartRoom service is constructed by one or several KPs. They interact by sharing information in the RDF format. The architecture for the required integration of presence service to the SmartRoom system is shown in Fig. 3.

SmartRoom space is maintained by Smart-M3 Semantic Information Broker (SIB). The presence sensor regularly sends its measurements to the backend processor. The corresponding KP runs on a dedicated computer. For the SmartRoom space,

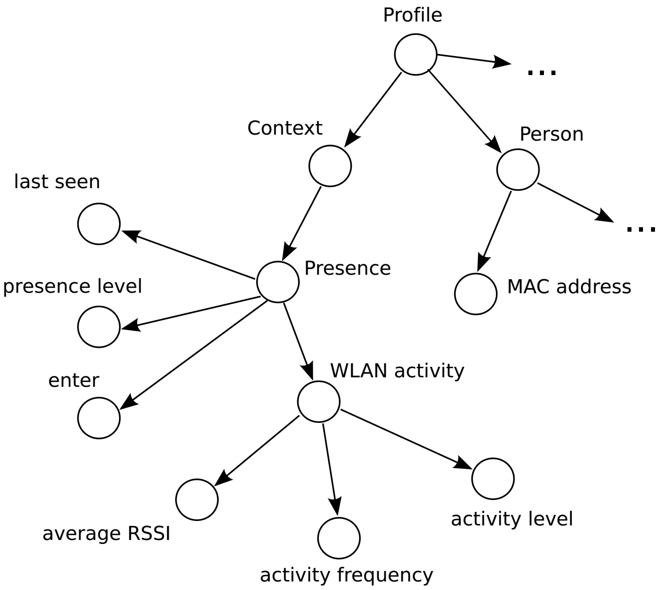

Fig. 2. Ontology of user presence (all relationships here are of type "has")

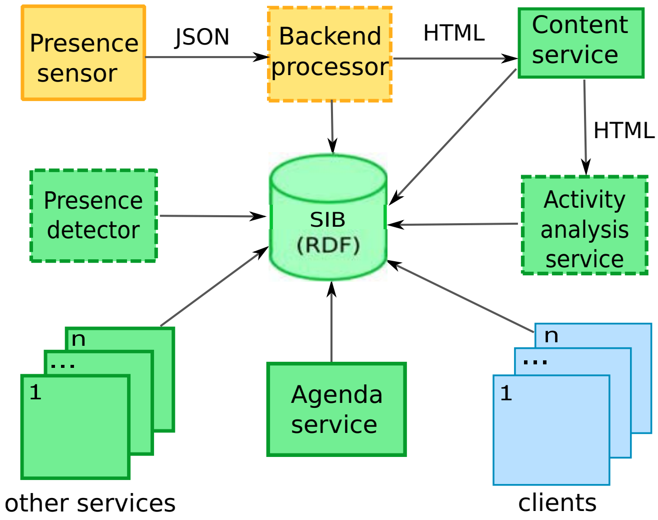

Fig. 3. Architecture of integration for the user presence information source (for the use in SmartRoom)

the backend processor is a KP that mediates data coming from the presence sensor to the SIB. For the presence sensor the KP is an HTTP endpoint; its implementation uses the flask web framework. This KP also interacts with the content service, which stores particular data from users and other services and allows to share this data with other SmartRoom space users using well-known file sharing technologies. The backend processor transferred data are MAC address, RSSI value and timestamp, which are then used for statistical processing and analysis of the user activity.

The presence detector is an additional KP. It subscribes for updates in the smart space on presence data of mobile devices. Any update is mapped to the related user using MAC address. The correspondence of users and MAC addresses is defined by the registration service. (Each user provides her/his MAC address only if she/he agrees.) The presence detector KP determines the user presence level based on the model of user presence state (see Section V below). This information is used then by other services (e.g., agenda service) in scenarios S_1 and S_2.

Activity analysis service is formed by one KP. This KP monitors the behavior of the system, analyzes the activity of users (e.g., the network activity, the real time speech) and main activities (e.g., the number of presentations). The service also visualizes suitable activity; its implementation uses the matplotlib library. At the end of the main activity or at the request service analysis of accumulated data from content service, i.e. calculates the following metrics of network activity: level of network activity, activity rate, and the average value of RSSI for each user. Activity analysis service is used or the implementation of scenarios S_3.

V. MODEL OF USER PRESENCE STATE

In the SmartRoom system, a user can be in different states of presence. Such a state reflects the status of participation in the ongoing activity. We introduce a coarse-grained model of user presence state. The model is depicted in Fig. 4 as a state

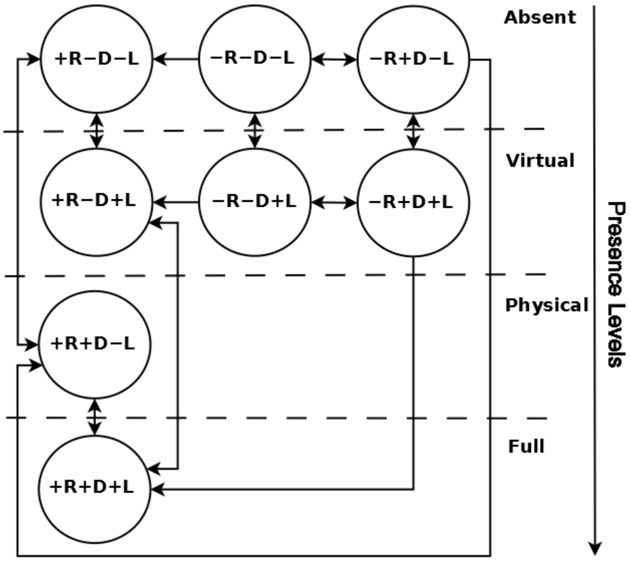

Fig. 4. Model of user presence state (R, D, L)

diagram. Each state $s = (R, D, L)$ has the following Boolean parameters.

R: whether the user is registered in the system (registered).

D: whether the presence sensor detects user's device in the room (detected).

L: whether the user is accessing the system using her/his SmartRoom client (logged in).

Clearly, the total number of possible states is $2^3 = 8$. Depending on the state the user presence can be classified into one of the following levels: absent, virtual, physical, or full. User cannot unregister herself/himself in the system. User may leave the room or stop accessing the system using her client. For instance in scenario S_2, the user status can be visualized on the activity agenda screen in dependence on the current presence level.

Consider the states when D is changing while R remains fixed (either registered or not). Scenarios S_1 and S_2 are based on detecting the transitions between such states. Scenario S_3 does not require instant presence detection, but for these scenarios the system can accumulate state of user presence over time for further analysis and reporting.

Scenario S_1 uses the unidirectional transition

$$+\mathrm{R} -\mathrm{D} -\mathrm{L} \;\rightarrow\; +\mathrm{R} +\mathrm{D} -\mathrm{L}. \tag{1}$$

User arrival is detected before starting the main activity. Then a welcome service is activated at once for this user, before her/his client is started.

Scenario S_2 uses the bidirectional transitions

$$+\mathrm{R} -\mathrm{D} -\mathrm{L} \;\leftrightarrow\; +\mathrm{R} +\mathrm{D} -\mathrm{L}, \tag{2}$$

$$+\mathrm{R} -\mathrm{D} +\mathrm{L} \;\leftrightarrow\; +\mathrm{R} +\mathrm{D} +\mathrm{L}. \tag{3}$$

They periodically happen after the first user arrival.

VI. Evaluation

We experimentally study possibilities and limitations of the proposed integration for use in scenarios S_1–S_3. For scenarios S_1 and S_2 we measure the time required to detect transitions (1), (2), and (3). For scenario S_3 we measure i) the amount of memory occupied by the statistics files and ii) the time of their processing with calculation of network activity metrics.

Scenario S_1: The evaluation consists of executing and measuring the following steps.

Step 1. The presence sensor determines a close device and sends the device presence data to the backend processor.

Step 2. For the first detection of device MAC address, the backend processor publishes presence data in the ontological form: one OWL individual (class Presence) with two data properties: last seen and enter.

Step 3. The presence detector monitors addition of individuals of class Presence or updates of data properties for existing individuals of this class. This persistent detection uses subscription. When such data are added or modified the presence detector computes the presence level and publishes the data property presence level.

Step 4. Any service that uses information on user presence (e.g., agenda service) subscribes to updates of the data property presence level.

The total execution time of these steps is the user presence detection time. This time cost is proportional to the number of detected users and depends on the given WLAN performance. The data publication and subscription operation are most expensive.

The measured time distribution is shown in Fig. 5, which characterize the performance of determining the presence of a single user. The sample size is 100 measurements. The average detection time is 677 ms. The high dispersion is due to variability in the network performance. Transmission of the data over the network takes the most share of the user presence detection time.

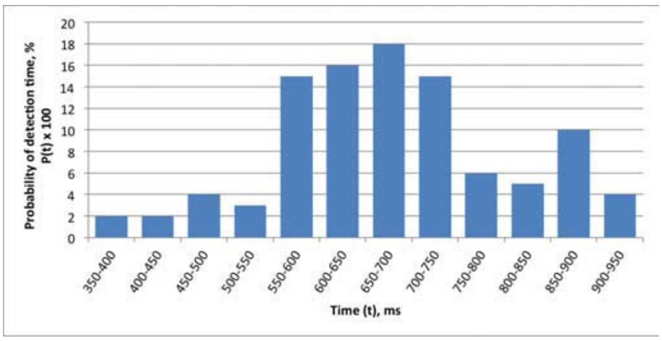

Fig. 5. Distribution of user presence detection time (for a single user)

Scenario S_2: The essential issue is the leave threshold. The Innorange technology does not allow immediate determination of whether the user left the room, so it is necessary to set a fixed value for the leave threshold, depending on the type of mobile devices.

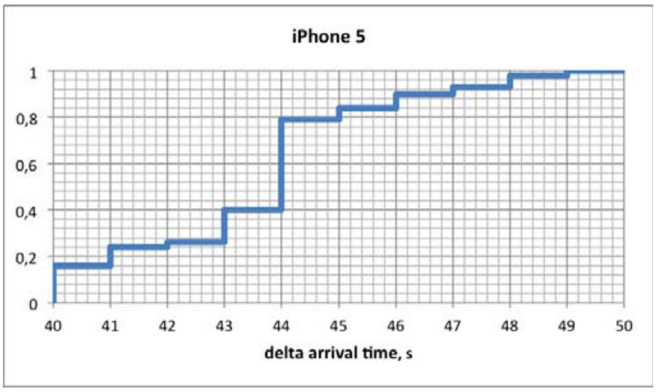

Fig. 6. Cumulative distribution of delta arrival time of probe requests frames: iPhone 5 (iOS 7.1)

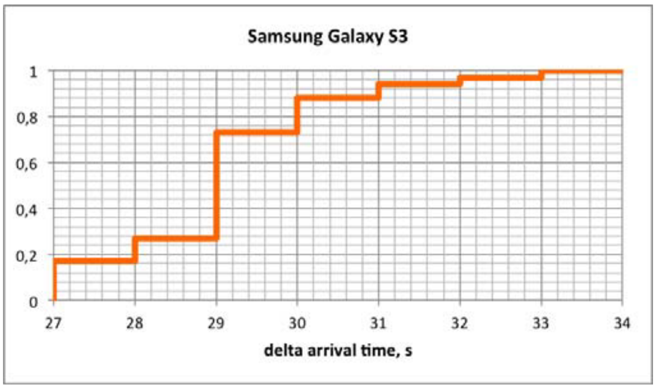

Fig. 7. Cumulative distribution of delta arrival time of probe requests frames: Samsung Galaxy S3 (Android 4.3)

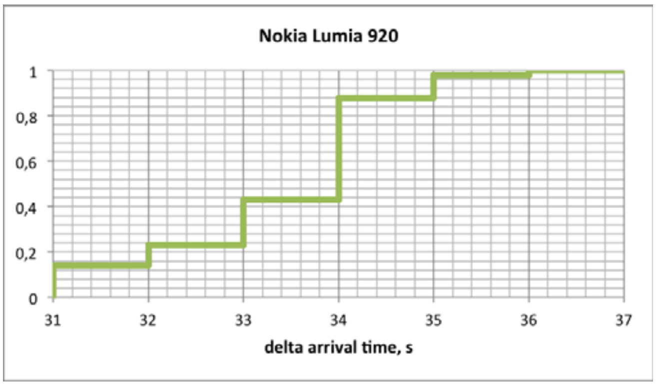

Fig. 8. Cumulative distribution of delta arrival time of probe requests frames: Nokia Lumia 920 (Windows Phone 8.0)

The leave threshold is the time elapsed before conclusion that the device (and its user) is physically absent in the room. We consider the following mobile devices: Nokia Lumia 920 (Windows Phone 8.0), iPhone 5 (iOS 7.1), Samsung Galaxy S3 (Android 4.3). Each of these smartphones periodically sends a probe request frame to determine which access points are within range (if WLAN is active and not used). The Innorange sensor is capable of tracking these frames and so it detects the presence of mobile devices.

Mobile devices periodically send probe requests with a frequency that is vendor specific. Since probe requests are used in the discovery phase that comes before the actual association to the access point, they are sent in the clear over all transmission channels in sequence. The emission frequency has been studied by monitoring a Wi-Fi channels and computing the delta arrival time, i.e. the difference between the arrival times of all the received probe request frames.

We measured the distribution of delta arrival time of probe request frames at specific smartphones. For all devices, observed around regular delta arrival time. For the iPhone 5 device delta arrival time was in the range $[40, 50]$ (Fig. 6), for the Galaxy S3 device – $[27, 34]$ (Fig. 7) and for the Lumia 920 device – $[31, 37]$ (Fig. 8). The values of high probability are: iPhone 5 – 45 s, Galaxy S3 – 30 s, Lumia 920 – 35 s. To simulate the user presence the devices are located about 5 meters from the presence sensor. Those results cannot be straightforwardly extended to all personal mobile devices, but they provide an idea on the period at which the probe requests are emitted by a Wi-Fi device.

For the time of the leave threshold we choose the upper bound of arrival time for used devices. In our case, it could be set to 50 s. Nevertheless, to allow for the maximum number of hits, we select 60 s. The presence detector monitors continuously the last seen property and reacts whenever its value exceeds the threshold. Thus the user is considered as absent in the room. Then the presence detector updates the property presence level. When the device is detected again, then the user is considered as re-joining the main activity (similarly as in S_1).

Scenario S_3: The content service is used for accumulation and analysis of statistics. The service is implemented as a web server. The backend processor creates and sends an HTTP request to the content service with the presence sensor measurements, if the RSSI values of each measurement exceeds the leave threshold, i.e., when the user is present.

Content service receives an HTTP request and generates on its basis the text file for each registered user. The text file for the user contains a set of rows, and the number of rows is determined by the number of the presence sensor measurement for the user device. Each line contains two parameters: timestamp and RSSI. At the end of the activity or at the request occurs the analysis of accumulated data, e.g., level of network activity, activity rate, and the average value of RSSI for each user.

Each measurement, and consequently a row in a user text file, corresponds to one WLAN unit sent by a user device. Thus the level of network activity is determined as $L_k = n_k$, where k is user index, n_k is the number of rows in the file of user k.

Another important metric is the activity rate. Given the number of measurements and their timestamps, we can calculate the activity rate of user k

$$\mathrm{f_k} = \frac{j - i}{t(s_{kj}) - t(s_{ki})}, \quad 1 \leq i < j \leq n_k, \tag{4}$$

where s_{ki} is i-measurement of k-user file, $t(s_j)$ and $t(s_i)$ are timestamps in j- and i- measurements.

Analysis of the activity rate determines when the participant is leaving the room. Let the leave threshold be 60 s, i.e., the activity rate is calculated every 60 s during the main activity. Our experiments show that if the activity rate is less than $0,017$ then the participant becomes absent in the room. That is, the value can be used as a bound. There is also dependence of the activity rate on the user type, such as "high active" or "low active".

To evaluate the performance we need to know the amount of memory occupied by the text files on the content service and time for processing and calculating the network activity metrics. During our measurements, an activity includes 10 speakers, every speech is lasted 15 minutes. The participants use their mobile devices to control the presentation and access to the presentations of others. At the end of the activity, the activity analysis service runs on a separate machine (CPU 2.30GHz, RAM 4Gb, Windows 7).

The activity analysis service operates with user statistics files on the content service and calculates the network activity level and the activity rate for each user. The average data processing time is estimated experimentally as $0,72$ s. The average size of a user statistics file is 346 KB. In sum, about 3500 KB of free space is needed on average to store the statistics files on the content service for 10 participants.

VII. Conclusion

This paper continued our development of SmartRoom system based on inclusion of user presence detection mechanisms for enhancing the intelligence of services. We employ the known method of passive radio detection based on its proprietary implementation in the Innorange technology. We focused on the three usage scenarios for SmartRoom, each defines a set of possible services. We proposed models for collecting and representing the presence information about the dynamic SmartRoom users. Our Smart-M3 based architecture allows using this additional source information by any SmartRoom service. We experimentally evaluate the proposed solutions, demonstrating the applicability and reasonable performance. The open source code is available at http://sourceforge.net/projects/smartroom/files/services/presence-service/.

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