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A cloud-IoT model for reconfigurable Radio Sensing: the Radio.Sense platform

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***Abstract*—In this paper we elaborate on the challenges that emerge when designing open IoT models and methods to enable passive "radio vision" functions within a cloud Platform-as-a-Service (PaaS) environment. Radio vision allows to passively detect and track any moving/fixed object or people, by using radio waves as probe signals that encode a 2D/3D view of the environment they propagate through. View reconstruction from the received radio signals is based on data analytic tools, that combine multiple radio measurements from possibly heterogeneous IoT networks. The goal of the study is to define the baseline specifications that are necessary to integrate this new technology into a cloud-IoT architecture. Following emerging semantic interoperability concepts, we propose an expressive ontology model to represent the radio vision concept and allow for interoperability with other systems. For accelerated integration of radio vision functions the open Radio.Sense platform is designed as compliant with existing models (oneM2M based ontologies).**

I. Introduction on Radio.Sense approach

Todays Internet of Things (IoT) relies on heterogeneous networks of sensing devices. Most of the existing IoT platforms, services and applications have been designed as isolated vertical solutions, in which all components are tightly coupled to the specific application context. Standardization activities are now facing the issue of interoperability, focusing in particular on communication technologies [1]. For example, an horizontal service platform for machine-to-machine (M2M) interoperability has been defined by ETSI [2] to provide a RESTful service capability layer accessible through open interfaces that are independent of the underlying network. However, a major challenge is *semantic* interoperability, as this requires different IoT platforms to be “understood”, which not only does include the communication level, but also the automatic interpretation of information coming from different platforms. Achieving IoT semantic interoperability is a challenging task [1], due to the heterogeneity of IoT sensors, the variety of data models, the implicitness of resource descriptions, as well as the limited accessibility of IoT platforms.

IoT platforms are now opening to the integration of new technologies. Among them, the radio vision [3]-[8] is emerging as a powerful technique to exploit radio-frequency (RF) signals - monitored within the network by the IoT devices - for sensor-free human-scale perception. The radio vision technology allows pervasive IoT networks to be converted into a dense multitude of radio imaging links that cooperate

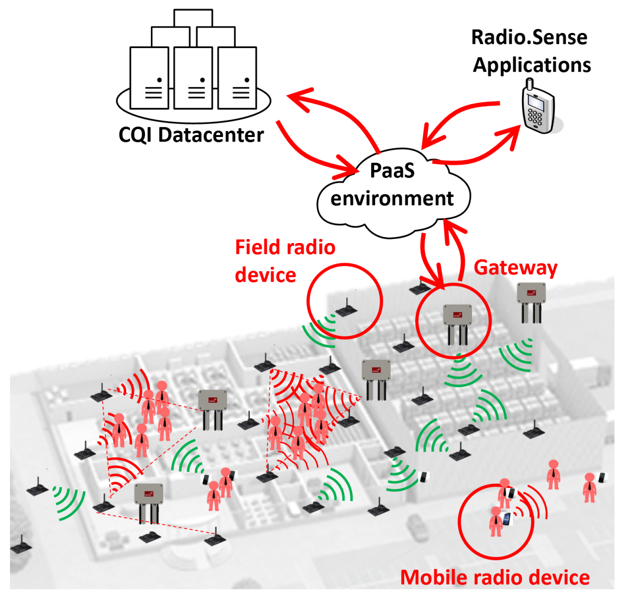

Fig. 1. Radio.Sense active/passive configurations and systems

to extract a three-dimensional (3D) view of the surrounding environment (cf. Fig. 1). RF signals commonly adopted for communications are in-fact perturbed by objects, body movements, and changing surroundings, as a result of the propagation of the electromagnetic (EM) waves and their interaction with the environment through reflection, scattering and diffraction phenomena. Therefore, the propagated RF signals not only transport the transmitted information but also encode a 3D view of all the objects that have been traversed by the EM waves. This implicit and mostly unused perception capability can be exploited in the IoT context by the analysis of the RF signals exchanged by heterogeneous IoT devices. In addition, it enables to attack in an innovative way the problem of the IoT interoperability, as well as the complicated interaction between heterogeneous hardware/software sensing resources.

The technology is based on the real-time processing of the Channel Quality Information (CQI) that is commonly used at the receiver-side to quantify the RF signal quality. The perturbations induced by moving bodies/objects on the EM

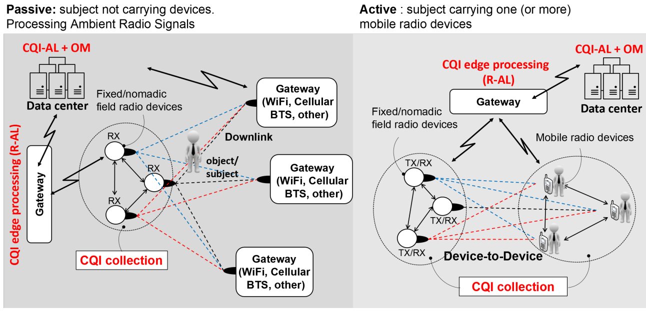

Fig. 2. Radio.Sense active/passive configurations and systems

wavefield can be measured directly from CQI data and processed to recover an image of the environment that originated these perturbations, without the need of any ad-hoc sensing infrastructure nor the cooperation of the monitored subjects (i.e., as for passive monitoring [4]). In radio vision, sensing emerges from dense networking. The technology serves as enabler for implementing a flexible sensing tool, paving the way for a new generation of IoT applications [11].

The goal of this paper is to investigate IoT methods and procedures supporting the integration of radio vision functions into a cloud-IoT platform, referred to as Radio.Sense and depicted in Fig. 1. The platform builds on a new class of methodologies to enable large-scale processing and management of CQI data in heterogeneous IoT networks, in conjunction with data analytics and cloud computing tools. We also propose an ontology model to represent the radio vision concept, namely to describe the relationship between "things" producing CQI data and "vision" information, allowing for interoperability with other IoT models [5]. The concepts of device, data abstraction and semantics are adopted to decouple IoT applications from specific low-level CQI processing implementation. All the Radio.Sense services are represented as virtual resources with uniform operations e.g., for CQI resource manipulation and inference.

The paper is organized as follows. Sect. II provides an overview of the radio vision technology. Sect. III illustrates the proposed Radio.Sense platform, while concepts of abstraction layers for IoT devices and CQI data-sets, and semantic interoperability through CQI object modeling are illustrated in Sect. IV and V. Some preliminary testing activities are presented in Sect. VI to reveal the potential of the Radio.Sense approach inside a smart space laboratory environment.

II. Radio Vision Technology: Overview

In radio vision systems, wireless receivers that are exposed to modulated EM fields, carrying digital/analog information, are configured to extract, process and share RF data in the form of noisy estimates of the time-varying channel response, or CQI. As illustrated in Fig. 2, in the proposed Radio.Sense platform, human-scale sensing emerges from the real-time CQI data analytics that run in the cloud, while pre-processing of data, as well as radio device abstractions (see Sect. III), can

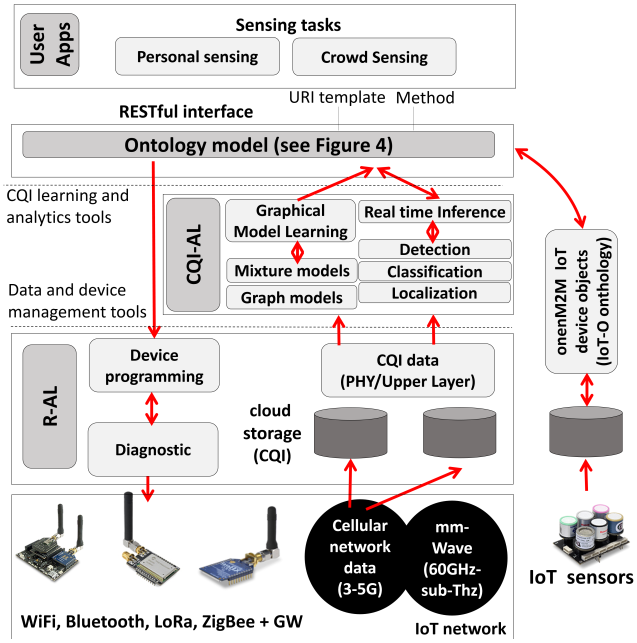

Fig. 3. Radio.Sense architecture summary: cloud services and object models.

be pushed to the network edge, represented by Gateway (GW) devices. The technology supports both active and passive configurations as illustrated in Fig. 2. The distinction between active and passive systems differentiates systems in which the active part (the RF transmitter) is under the control of the system from those where it is not.

Passive systems capitalize on pre-existing network infrastructures where densely air-interacting IoT devices are exposed to some EM wave-fields that are continuously maintained for wireless communication tasks, and capture those ambient RF signals [10]. CQI processing might be carried out distributedly or centrally while body recognition is obtained by real-time monitoring of the body-induced radio propagation alterations/perturbations [8].

Active systems exploit dense communications with mobile transmitters acting as interconnected mobile probes. Mobile probes might be physically co-located with the subject (wearable or wrist-worn devices, or personal devices such as smartphones/tablets) or being part of a mobile network infrastructure [14]. These systems might also rely on a decentralized architecture where user data can be propagated in direct mode (e.g., BLE or ZigBee radio technologies) instead of through a remote service provider (e.g., cellular base stations [15], WiFi access points [9]).

III. The Radio.Sense Platform and Methods

The approach followed in this section is to lay the groundwork for the integration of radio vision technologies into existing IoT frameworks as well as to deliver the common specifications for new data models that can be harmonized with existing IoT models. The new sensing paradigm is integrated within a platform-as-a-service cloud model (PaaS) to enable a wide range of applications. The platform consists of the following components (cf. Fig. 1).

Field radio devices. The individual mote devices for the creation of multi-standard wireless sensor networks. Devices can integrate different radio technologies to collect radio signals of different types.

Mobile radio devices. Personal mobile devices, wearable or wrist-worn devices acting as mobile probe RF signal generators and connected to a network infrastructure.

Gateway devices (GW). Provide access point and sink node functions for radio device boards supporting different RF interfaces. They also act as CQI data collector and interact with the data center unit through the abstraction layers (Sect. IV). In active systems, each deployed GW device serves as fixed probe RF signal generator so to maintain the RF field continuously, and tracks any alteration of the radio propagation environment. The GW device also acts as over-the-air (OTA) updater for controlling the CQI data collection process and might also integrate edge computing functions (e.g., for managing radio device data).

Data center unit. Consists of a PaaS runtime environment to deploy and efficiently execute cloud components of large scale applications. The PaaS runtime environment should be designed to enable near real-time processing of heterogeneous CQI data streams. The PaaS allows treatment of semantic information built upon the Radio.Sense CQI models (Sect. V).

The Radio.Sense architecture in Fig. 3 can be viewed as a three-tier system consisting of: 1. the device abstraction layer providing a southbound interface to individual IoT devices producing CQI data and controlled by the OTA control plane; 2. the CQI data layer, providing a common API for data processing; 3. the ontology layer, where CQI data object models can be defined and instantiated by end-user applications, acting as an intermediate layer between user-defined, or third party, applications and the underlying abstraction layers.

In what follows we describe the software layers of the proposed platform. Device and data abstractions (Sect. IV) let the cloud to interact with the radio devices and CQI data processing at a higher abstraction level. The ontology model (Sect. V) aims to propose reusable object models for interaction with low-level device and abstraction layers, as well as for northbound communication with the application software.

IV. Radio device and CQI data layers

We present an abstraction layer that allows to manage low-level CQI information as well as real-time inference, handling different IoT radio devices (e.g., over different RF bands) and based on data collection rules instructed by the OTA control plane (Sect. V-C).

A. Radio device abstraction

The radio abstraction layer (R-AL) is designed to allow the Radio.Sense cloud platform to interact with the radio hardware at an abstract level, with the purpose of programming specific radio functions (if applicable) or managing CQI data of different types. Data collection is based on the following categorization of the CQI measurements (referred to as CQI_TYPE):

i) physical layer (PHY) channel quality information at baseband symbol level, including channel state information (CSI), and received symbol quality [6];

ii) upper layer (UL) network/link-layer received signal strength (RSS) [4], [3] or other aggregated channel quality information including packet error rates or related metrics, and link quality information (LQI);

iii) raw signals (IQ) that include raw features such as micro-Doppler measurements, dynamic phase shifts and IQ channel envelope [12].

R-AL also implements OTA programmable radio functions (OTA_FUNCTION) whose reconfiguration can be triggered by the control plane and used to modify the CQI data collection process, with the purpose of reconfiguring the sensing task itself. Specific low-level radio functions that can be subject to reconfiguration are defined in Table I.

B. CQI data abstraction

The CQI data abstraction (CQI-AL) decouples the application-dependent sensing tasks from the pre-processing of raw CQI data that is needed to isolate relevant patterns inside heterogeneous CQI structures. Compared with conventional IoT applications, the adoption of radio vision functions allows to define a unified approach to human-scale sensing problems that are based on real time processing of *CQI features*. These features are "low-dimensional" representations of CQI data, as they describe the statistical interrelations among the different CQI time series, obtained from different physical links $\ell_j \in \mathcal{L}$ (devices or antennas) and frequencies $f_i \in \mathcal{F}$ (or sub-carriers, if applied to multi-carrier radio interfaces). Features (CQI_FEATURE) can be generally classified as: *i)* EM attributes, including CSI and IQ-type features; *ii)* statistical attributes, including average RSS and LQI, standard deviation, statistical correlation, probability mass function; *iii)* anomalous patterns, recurrent CQI data variations, spikes, peaks or series.

Graphical models offer a powerful framework for relating these features to the process to be sensed. Each feature is here abstracted as a random signal defined over a graph, where the graph represents the topology of the underlying interactions between features and sensed process, and inference is solved by sophisticated Bayesian algorithms based on the knowledge on such topology. For example, graph theory allows to model the structural relationships existing between CQI samples over time, space (links) and frequency. In addition, the combination of graphical models with mixture models provides useful properties that make them attractive as a general tool [17]. Considering the CQI feature vector $\mathbf{s} = \{s_v\}_{v=[f_i,\ell_j,t]}$ as the input data-set structure for recognition, each individual observed feature $s_v = s_{f_i,\ell_j,t}$ is extracted using the R-AL interface and is a function of the time instant t (which selects the data within the time window $[t, T-t]$), the frequency f_i

OTA_FUNCTION	Reconfiguration description
One-hop neighborhood	number of active links to cover a detection area, or device-to-device neighbourhood
Frequency and bandwidth	operating carrier frequency/channel (subcarriers for OFDM radio interfaces)
Transmission duty cycle	time interval between two consecutive radio transmissions that rules the RF signal emission rate
CQI type	reconfiguration (where applicable) of the CQI type - PHY, UP, IQ
CQI sampling	reconfiguration of the CQI sampling (during debugging)

TABLE I
SELECTED RADIO FUNCTIONS FOR OTA PROGRAMMING PROFILES.

and the link ℓ_j. For a selected sensing task τ_i (see Sect. VI), the objective is to infer a latent process z (e.g., people location, movement, behavior or spatial occupancy), that is hidden in the observed data and is relevant to the sensing task. The process is inferred by defining a stochastic model $\mathrm{M}(\mathbf{s}|\tau_i)$ for the joint distribution of the CQI features $\mathbf{s}$, as a mixture of graphical structures:

$$\mathrm{M}(\mathbf{s}|\tau_i) = \sum_{k=1}^{m} \alpha_{k,i} \mathrm{G}^{k,i}(\mathbf{s}|\tau_i), \tag{1}$$

with $\alpha_{k,i} = \Pr(z = k|\tau_i) \geq 0$, namely the mixture coefficients, representing the prior knowledge on process z, which takes value $k \in \{1, ..., m\}$ with probability $\alpha_{k,i}$ and $\sum_{k=1}^{m} \alpha_{k,i} = 1$. Joint probability distributions $\mathrm{G}^{k,i}(\mathbf{s})$ are the mixture components. The mixture model (1) selects, for a particular sensing task τ_i, the most appropriate graphical model to describe the input feature set $\mathbf{s}$. Each k-th mixture component $\mathrm{G}^{k,i}(\mathbf{s})$ can have a potentially different graph structure $\mathcal{G}_{k,i} = \{\mathcal{V}, \mathcal{E}\}$, with nodes $v \in \mathcal{V}$ and edges $\mathcal{E}$, and it could be assumed as following the local Markov property $\Pr(s_v|\mathbf{s}_{\mathcal{N}(v)}; \tau_i) = \Pr(s_v|\mathbf{s}_{\mathcal{V}/v}; \tau_i)$, where $\mathcal{N}(v)$ is the open neighborhood of node v.

The CQI-AL provides the upper ontology layer (Sect. V) with the parameters characterizing the graph structures $\{\alpha_{k,i}, \mathcal{G}_{k,i}\}$ for each defined sensing task τ_i. Learning of mixture structure (1) can be obtained from training data and can be generally solved based on expected-maximization (EM) algorithms: simple solutions exist for tree distributions as mixture components $\mathrm{G}^{k,i}(\mathbf{s})$ [19], while application to more complex dynamic Bayesian networks [20], Markov and conditional random fields [21] is still considered as an open problem. Real-time detection, and inference services can be implemented based on a database of learned structures. Basic inference problems (including detection and classification) on graph structures (1) correspond in general to infer the value of the hidden variable z as

$$\Pr(z = k|\mathbf{s}; \tau_i) = \frac{\alpha_{k,i} \mathrm{G}^{k,i}(\mathbf{s}|\tau_i)}{\sum_{h=1}^{m} \alpha_{h,i} \mathrm{G}^{h,i}(\mathbf{s}|\tau_i)}, \tag{2}$$

now for new input features $\mathbf{s}$.

V. ONTOLOGY MODEL FOR CQI DATA

In this section we define a common set of object models (OMs) to enable applications to interact with the low-layer CQI data and analytic tools, as well as to communicate with devices over diverse transport and application protocols, subject to the provided authorization and permission controls.

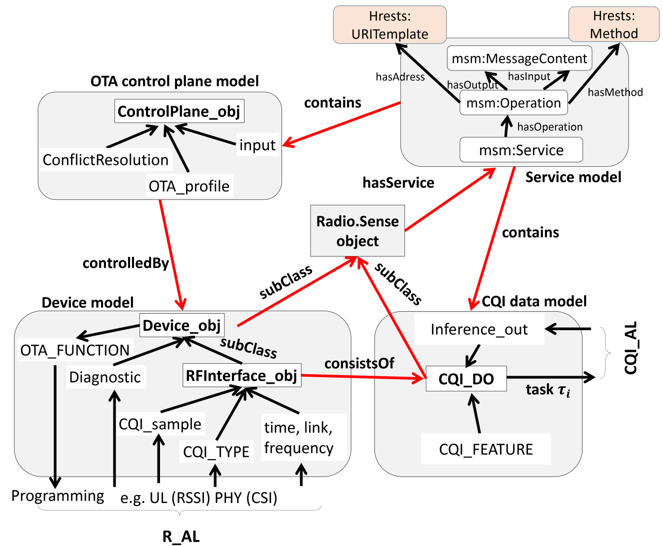

Fig. 4. Radio.Sense ontology model for CQI processing and management.

OMs use oneM2M design patterns [5], and thus provide full interoperability with standard IoT data objects running inside the cloud. As described in the following, and depicted in Fig. 4, OMs provide an abstract representation of: i) a device or a group of devices with common functions (e.g., using the same radio front-end or technology, producing CQI samples of the same type, etc.); ii) the CQI data set that contains measurements from multiple devices; iii) the service model that defines the cloud services as combinations of elementary sensing tasks and iv) the OTA control plane for CQI data collection and sensing task reconfiguration.

A. Device and data models

The component CQI Data Object (CQI-DO) acts as the digital counterpart of networks of physical devices producing CQI data for sensing purposes: it can run in the cloud or inside the Gateway components. The CQI-DO manages an abstraction of the physical devices by means of a description of its RF interface (RFInterface_obj in Fig. 4) that, in turn, contains context information, such as location, link, time, and frequency information, supported configurable networking functions (Table I) and CQI_TYPE. Such information is obtained by interacting with the R-AL. In addition, CQI-DO directly interfaces with the CQI-AL: it thus implements an assigned sensing task τ_i and processes the real-time inference results (2) for the input CQI features.

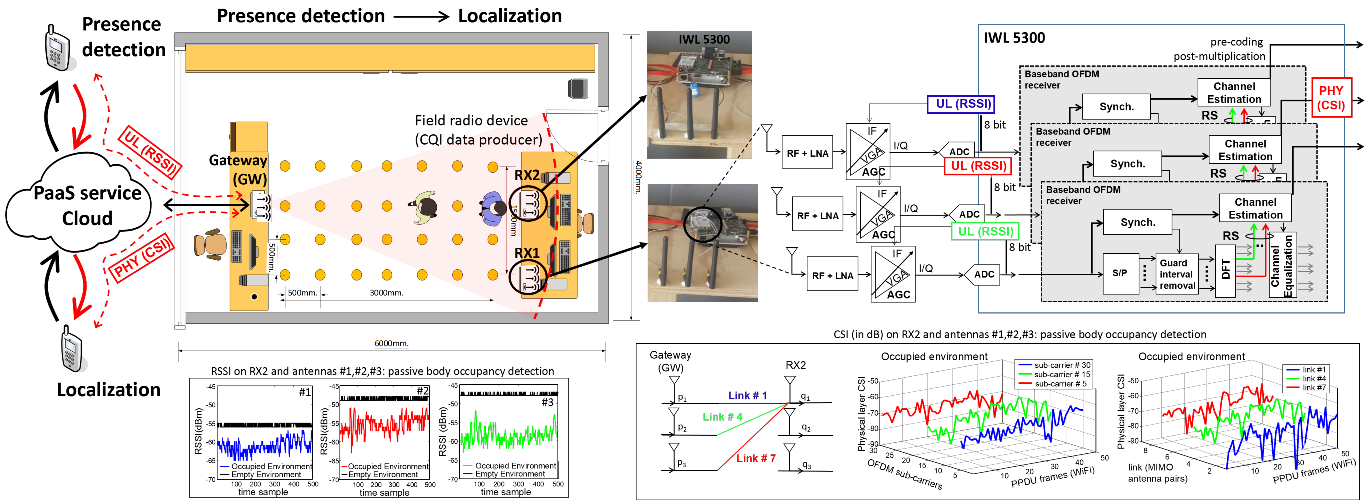

Fig. 5. Layout for preliminary tests: RSSI and CSI extraction, example of sensing task reconfiguration (presence detection and localization).

B. Service model and sensing tasks

OneM2M provides a base ontology [5] with the aim to help non-oneM2M compliant data models to derive oneM2M concepts to describe their data model and enable seamless interactions between end-user applications and services. Therefore, it is important to represent how services can be requested, without any ambiguity in order to reduce the amount of manual effort required for discovering and using them. Here, we select the minimal service model (msm) ontology [23] to describe services since it provides a common vocabulary based on existing web standards able to capture the core semantics of both Web services and Web APIs in a common model. Each service is described using a number of operations that have address, method, input and output Message Content descriptions. In particular, the msm:Service (Figure 4) provides an abstract representation of the cloud services by means of a description of their functionalities. Any cloud service is defined as the composition of multiple sensing tasks τ_i and thus requires the cooperation of multiple CQI-DO objects. The msm:Service is also in charge of maintaining and possibly terminating the relationships between various CQI_DO objects, in order to improve any service operations. In accordance with previously proposed ontologies for M2M applications, the service model provides methods for the distributed allocation of tasks for the execution of applications in the Radio.Sense scenarios between objects that can perform the same sensing operation in a given geographical area. Notice that reconfiguration of sensing tasks, might cause conflicting requests from different Radio.Sense applications and users that should not impact/interfere with each other. The developed middleware should thus pay attention to the relations among Radio.Sense applications, conflicting users (and situations as well) and available CQI objects/resources around.

Sensitivity	Specificity	Accuracy	False positive rate
0.83	1	0.88	0

TABLE II
OCCUPANCY DETECTION PERFORMANCE (RSSI BASED).

Localization	RSSI	CSI
RMSE (m)	0.69	0.93

TABLE III
LOCALIZATION RMSE FOR SINGLE TARGET TRACKING: RSSI AND CSI.

C. OTA control plane

The Radio.Sense platform implements the OTA reconfiguration of the application code through the ControlPlane_obj and Device_obj resources. The corresponding model is summarized in Fig. 4. Programming and updates are based on the delivery of single/multiple code modules (e.g., low-level firmware or upgrades) to single/multiple destination receivers. Each code module implements a specific OTA profile (Table I) that maps onto a target OTA_FUNCTION and sensing task. OTA profiles address various networking protocol features, such as routing, connectivity, frequency/bandwidth, power and device duty cycling. The application of any OTA profile results in an ad-hoc modification of the CQI data collection process which, in turn, triggers the reconfiguration of the sensing task itself or a modification of its accuracy.

In the proposed platform, the Gateway (GW) devices act as OTA updater, while radio device boards (field devices) act as OTA update receivers. The transport protocol for OTA programming can be chosen based on [13]. In the following example, the control plane is employed to modify the CQI type, based on the implementation of a WiFi network.

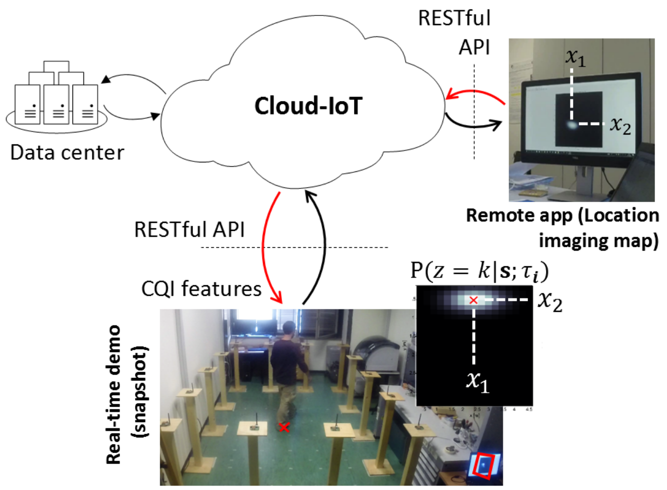

Fig. 6. Top. Passive subject tracking and imaging app (snapshot from video records). Bottom. Remote localization service: layout for Gateway and field devices (IEEE 802.15.4).

VI. Preliminary validation

The core services defined by the Radio.Sense platform are divided into *personal* and *crowd* sensing. Personal sensing is the focus of the below case study and covers various tasks that monitor different aspects of a person's "social settings" such as proximity/presence detection, passive or device-free localization [3], behavior recognition, and health related conditions [6]. Crowd sensing focuses on multiple people, including counting and density monitoring [22].

In the example summarized in Figure 5, we employed a network of WiFi devices working in the 5.32GHz band (i.e., WiFi band 2, channel 64 and nominal bandwidth 20 MHz). A single GW device is programmed to inject (or transmit) custom IEEE 802.11n PHY protocol data units (PPDU) structured as standard high-throughput (HT) greenfield WiFi format, including preamble, MAC addresses, header, and payload. Injected frames are sent at every 10 ms and received by two field devices (i.e., RX1 and RX2). The chip-set firmware and kernel [24] were used to obtain CQI samples of received IEEE 802.11n data frames. Monitored CQI types can be in the form of RSSI (UL) and CSI reports (PHY). The considered WiFi chip-set reports the RSSI values from 3 antennas and the CSI for a subset of 30 OFDM sub-carrier groups, over the active MIMO links (considering the GW equipped with 3 antennas). Both CQI types are represented by a CQI_DO object and therefore can be selected by end-user applications based on the specific usage scenario.

The considered scenario focuses on a personal sensing service. RSSI features are continuously monitored to detect the presence of the subject (human body) in the area: when human presence is detected, the CSI reports from field devices are requested by the GW node to extract the finer-grained position of the newcomer subject. Compared to RSSI, CSI reports have larger size, therefore they should be triggered only on-demand. In Tables II and III we summarize the results obtained for occupancy detection and localization separately, using RSSI and CSI. Table II shows occupancy detection performance in terms of sensitivity, specificity, accuracy and false positive rate, considering single and double targets located at different positions. Occupancy detection is based on the real-time evaluation of the RSSI correlation among co-located antennas of the same device. The use of RSSI is accurate enough to discriminate an occupied environment from an empty one (observed sensitivity is 0.83). Instead, as depicted in Table III, target localization accuracy obtained from CSI reports is remarkably larger compared to RSSI. Finally, it is worth noticing that the highlighted performance have been observed by using only two MIMO devices.

In Fig. 6 we show that better performance can be obtained at the expense of a larger number of devices, and CQI reports to be processed. In the example, a real-time passive localization service is implemented based on a network of 14 IEEE 802.15.4 field devices (operating over 2.4GHz) that are pre-installed inside the monitored area (as shown in the bottom figure). The passive subject tracking service is made accessible remotely by an end-user application (top-right corner subfigure) running on a portable device. We use a JSON REST (Jax-RS web services) framework to encode the CQI features before sending to the cloud. Probabilities in (2), where latent variables z are here interpreted as monitored positions, are pushed to the application and are mapped on 2D coordinates in the space, to reconstruct the image onf the environment. Tracking accuracy and latency (not shown) can be scale down to 0.3m and 100ms, respectively.

VII. Conclusions and future work

The paper described the architecture of the Radio.Sense software, that allows building a cloud platform, the baseline IoT methods and procedures to support the integration of radio sensing and vision functions. At present, we are designing the network layer protocols for the control plane and the service layer, by taking into account the findings of the experiments described in Section VI. Future work will address methods for efficient triggering of tasks as well as conflict resolution.

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