Wireless Cloud Network for Augmented Communication and Sensing in 5G Massive Industrial IoT

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***Abstract*—Driven by the fourth industrial revolution (Industry 4.0), future and emerging Internet of Things (IoT) technologies will be required to support unprecedented services and demanding applications for massively dense machine-type connectivity, low latency, high reliability and distributed information processing. In this article, we describe a novel approach to IoT architectures based on a wireless cloud network (WCN) platform that can lease advanced communication and sensing services to off-the-shelf industrial wireless devices via a dense, self-organizing *cloud* of wireless nodes. The paper introduces, at first, the proposed architecture and illustrates an experimental case study inside a pilot industrial plant evaluating the proposed architecture performance based on cooperative communication. Next, it gives an overview of consensus-based distributed signal and information processing algorithms. Finally, human body localization and radio vision applications based on distributed processing of wireless signals are investigated to support future and emerging human-machine interaction modes.**

I. Introduction

The next generation Internet of Things (IoT) is expected to be underpinned by 5G wireless communication technologies. Considering the exponentially increasing number of IoT devices [1], in the near future wireless IoT networks will become topologically dense, with huge numbers of complex interactions taking place and evolving towards self-organising architectures. For example, current industrial automation trends towards Industry 4.0 paradigms are driving the transformation of factories into highly flexible and reconfigurable production systems, where radio technologies will play a crucial role only if paired with advanced solutions to support massive machine-type communication (mMTC), ultra-reliable and low latency data publishing, as well as applications demanding for self-organization and advanced distributed sensing capabilities. Commercial-off-the-shelf (COTS) IoT technologies designed for industrial set-ups [2], [3], namely Industrial Internet of Things (IIoT), support long-term deployments while communication protocols are primarily designed to maximize battery lifetime [4] or optimized to handle periodic or non-critical traffic [5]. To allow wider adoption of wireless networks in an industrial context, a substantial technology innovation is thus required in terms of new types of devices embedding a large set of functions in a decentralized fashion such as self-configuring and learning protocols, communication and computing strategies to support delay/safety-critical applications. Although the majority of existing wireless network designs focus on energy consumption, recently some works have begun to underline the crucial role of optimizing latency and reliability as these requirements are essential to support mission-critical applications (see [5] and references therein). Even if experimental validations [6] and comparative analysis [7] confirm the potential of these emerging solutions, their practical deployment to replace an existing industrial network is still to be addressed.

In line with the above scenarios, the design of both wireless physical (PHY) and medium access control (MAC) layers of the next generation IoT systems, is arguably the most challenging and problematic task as it must be built on fundamentally different principles that support and enhance the functionality of the entire network: such principles should exploit the complexity of the network topology and embrace dense and massively-interacting communication paradigms. In this paper, we describe a new approach to wireless IoT based on a dense cooperative wireless cloud network (WCN). As shown in Fig. 1, advanced communication and sensing services can be transparently provided to COTS devices via a dense, self-organizing *cloud* of wireless nodes. In this cloud, information is forwarded via multiple relays to the intended destinations using cooperative communications and distributed signal processing tools. Network organization, and management (i.e., multiple access in a shared spectrum), as well as sensing tools are fully decentralized. COTS devices at the edge are blind to the inner workings of the cloud. They can access to cloud services through cloud access nodes while the cloud is able to self-organize to provide augmented services on-demand.

The WCN concept goes beyond theory, in fact it has been actively developed and demonstrated by the DIWINE project (http://diwine-project.eu/public), focusing on several industry-scale applications [8]. To support WCN functions, distributed signal processing is crucial to let the nodes acquire the network-state information necessary to set up the cloud functionalities and self-organize without the support of any

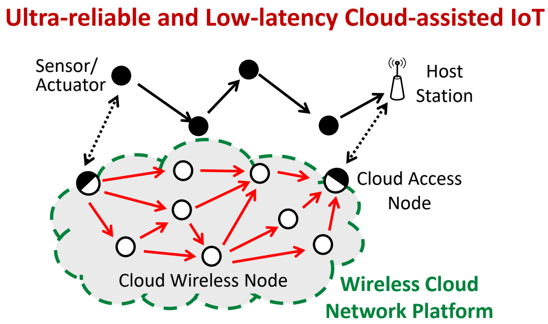

Fig. 1. Cloud-assisted industrial IoT architecture underlaid with a distributed and self-contained wireless cloud network platform.

central coordinator. On the other hand, centralized algorithms require each node to broadcast the raw data to a fusion center (FC), which is responsible for processing and sending back the outcome to all nodes. Although they guarantee optimal performance, these solutions are penalized by the latency and communication/computational overhead required for data aggregation/processing at the FC, that badly scale with the network size. Furthermore, they are vulnerable to device failure at the FC or closely located nodes. Distributed algorithms enable the devices to fuse their sensed data and infer the desired information relying solely on local processing and interactions with neighbors. Such interactions can be exploited to infer, or learn, patterns of interest that are hidden in the data sparsely observed by the devices (or agents), make collective decisions, reveal relationships or recognize behaviors of interest. Even if each agent may not be capable of sophisticated behaviors on its own, the combined action of all agents allows to solve complex tasks.

The paper is organized as follows. In Sect. II we review the WCN architecture and give details of a practical demonstrator that has been evaluated inside a testing pilot industrial plant [9]. In line with the 5G evolution, a multi-RAT (Radio Access Technology) architecture is discussed for critical process monitoring, where cloud nodes (CNs) employ IIoT wireless standards to interface with the field devices and an ad-hoc cooperative system for reliable intra-cloud communications. Next, in Sect. III, we summarize the theoretical underpinnings of intra-cloud distributed processing to support augmented sensing and control functionalities. In Sect.IV, consensus-based network localization and device-free radio sensing of the environment through radio frequency (RF) signal inspection is described. We finally conclude by summarizing open issues and future developments.

II. Wireless Cloud Network Architecture for Industrial IoT: Network Functions and Validation

In this section we describe the platform that integrates the WCN functions with an industry-standard wireless sensor network implementation. In particular, as described in Fig. 2-(a), the proposed platform consists of wireless field devices underlaid with a distributed and self-contained network of CN that can lease advanced networking functions to standard industrial field devices upon request. Here, the field devices comply with the WirelessHART [10] standard (IEC 62591). Cloud devices autonomously self-organize to meet specific service requirements not supported by existing industrial systems. The proposed WCN design points towards a disruption of the *host-centric* structure of current IIoT standards in favor of *device-centric* architectures, which exploit intelligence also at the field device side to incorporate distributed services on demand. Cloud radio modules are equipped with a dual RAT. The first radio technology guarantees backward compatibility with the WirelessHART air-interface, as well as device authentication with the Host station, which controls the industrial monitoring functions [9]. The second radio technology supports the new cloud functions and adopts a proprietary radio interface. The cloud access (CA) nodes provide an interface to industrial field devices requesting cloud services and seamless traffic off-loading. Communication among CA nodes (field-side CA-F and Host side CA-H nodes, respectively) is implemented by cooperative transmissions. In what follows, we describe the implemented functions for networking inside the cloud and the experimental validation in an industrial plant.

A. Networking Functions for Low-latency Data Publishing

Current industrial wireless solutions [2] support few critical applications, with limited scheduling options due to an optimized design for energy consumption and deterministic traffic management. In addition, unlike wired communication solutions (*i.e.,* CAN, Fieldbus), the radio link quality is typically impaired by harsh environmental conditions (*e.g.,* building blockage, metallic obstructions, interference) that often impose a certification of the communication reliability through network planning optimization tools as well as post-layout verification [11]. As a result, some relevant mission-critical *data publishing* workloads required in specific applications are more difficult, and in some cases impossible, to handle.

Data publishing happens when the field device detects some relevant conditions that generally require either a low-latency reaction, a highly reliable or a high-throughput data transfer. In the example of Fig. 2-(b), a *low-latency* data publishing task is leased to the WCN: the CA nodes handle asynchronous events taking place either at a remote wireless field device or at the Host station (or both), so that suitable corrective actions can be applied. The availability of a low-latency *upstream* (field device to Host) and *downstream* (Host to field device) data forwarding mechanism also enables the fast exchange of request-response messages, typically consisting of few datagrams.

As summarized in Fig. 2-(b) (on the left), communication among the CNs takes place over a series of contiguous, synchronized slots of 10 ms each, organized in super-frames of 8 slots and hyper-frames collecting a data publishing transaction (or communication session) of 16 consecutive super-frames. CA devices interfacing with the cloud is implemented over 6 contiguous channels (data publishing channels - DPCH). Two shared broadcast channels (SBCH) are also configured

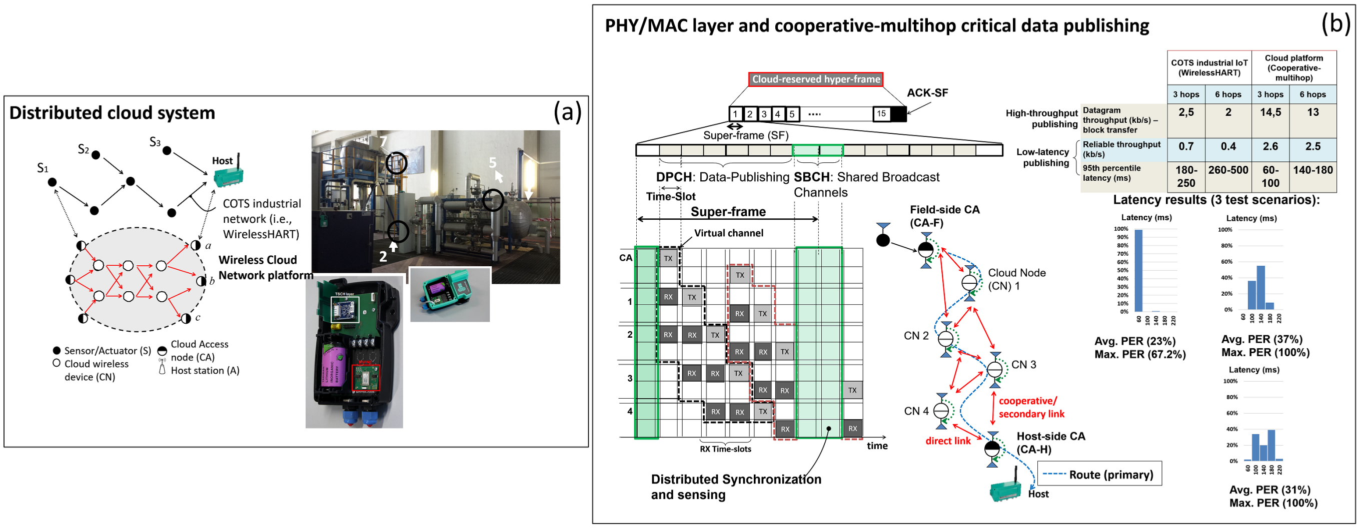

Fig. 2. (a) WCN architecture: dual radio technology (RAT) implementation with battery-powered CN prototypes (courtesy of Pepperl+Fuchs). (b) Cooperative-multihop message passing, chain-start, chain-end and ACK superframes. Latency and throughput comparison with COTS IIoT designs: a standard WirelessHART network (IEC 62591) is used as benchmark for performance comparison.

inside each superframe to propagate CA control/configuration functions as well as to implement distributed sensing tasks. More details are given in Sect. IV. Focusing on data publishing, a sequence of cooperative transmissions is implemented to connect source and destination CA nodes, where cloud devices act as intermediate decode and forward relays [12]. The cooperative link abstraction consists of separate radios encoding/transmitting or decoding/receiving messages in coordination [13]. Experimental validations in controlled laboratory environments (*e.g.,* see [14]) showed that such systems could achieve enhanced reliability compared to standard multi-hop solutions as mimicking the performance of a wired system. Despite some recent attempts to develop cooperative relaying features tailored to wireless IoT networks [15], practical methods to integrate such schemes into an industrial standard are still missing [9].

In the proposed set-up, validated in the next sections by experimental trials, the communication among the CNs takes place over consecutive DPCH slots. Within each slot, a single cloud device can thus transmit while selected CNs along the route path can receive in *multicast* mode. The cooperative algorithm allows an *implicit-retry* capability resulting from its multiple packet propagation and receive opportunities. In more details, the CA source node tunnels the input datagrams through the cloud section: each CN here handles data forwarding by *duo-cast* mode (*e.g.,* transmitting the same datagram/packet towards the two following nodes in the route path), up to when the CA destination node is reached. Thus, each packet always has two propagation opportunities and, similarly, the destination node has always two packet receive opportunities, corresponding to a *cooperative diversity* order [16] of 2. In what follows, the performance indicator adopted for performance assessment is the latency (*e.g.,* 95-th percentile), measured with respect to the first successful datagram reception.

B. Experimental Validation

In Fig. 2-(b) (on the right), latency and throughput results are discussed by collecting measurements obtained in different sites within a testing industrial plant described in [9]. For all cases, the proposed distributed system handles the delivery of data acting as a *hardware as a service* (HaaS) provider and implementing the cooperative forwarding scheme previously described. The goal is to experimentally verify, in a real-world testbed, the performance of the cloud section as specifically tailored as a complement to regular IIoT designs. Unlike previous proposals [17], the CNs are here designed to augment conventional industrial network functions and they can lease extended services to pre-existing industrial equipment, upon request. The PHY layer of the CN transceiver complies with the IEEE 802.15.4e [10] and operates over the 2.4GHz band. However, it is configured to double the data-rate (500kb/s) to ensure a substantial publishing rate increase.

System validation shows substantial improvements compared with standard single-path source routing (IEC 62591 compliant) solutions. An order of magnitude increase of throughput was made possible by the cloud (in the range 2-4 Kbyte/s), while a twofold increase in packet delivery rate has been observed in most of the investigated settings. The table of Fig. 2-(b) (on the right) provides a summary of the achievable figures, focusing on high-throughput datagram transfer (kb/s), reliable throughput for request-response messages (kb/s) and corresponding 95-th percentile latency (ms). For each case, the cloud platform performance is compared with current COTS implementation (WirelessHART), for typical 3 to 6-hop topologies.

The use of the multihop-cooperative transmission chain provides a sufficiently high level of immunity to multipath

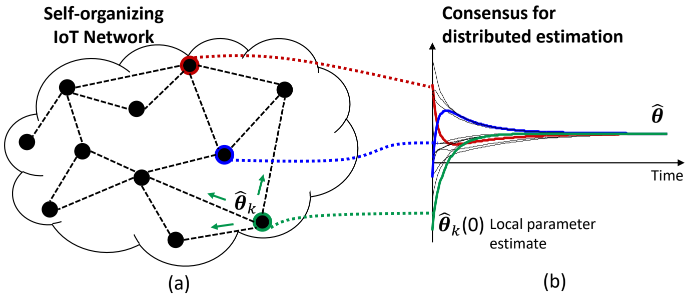

Fig. 3. (a) Self-organizing IoT network; (b) Example of distributed consensus for the estimation of parameters $\boldsymbol{\theta}$.

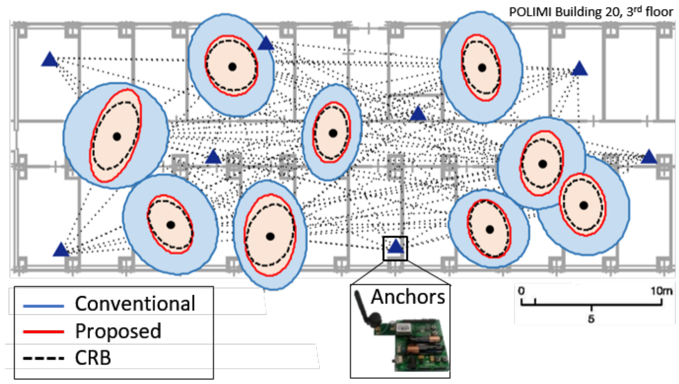

Fig. 4. Consensus-based localization in indoor scenario with 17 nodes based on IEEE 802.15.4 standard including 8 anchor nodes and 9 devices for localization purpose. The proposed consensus-based method (orange ellipse) outperforms the conventional approach (light blue ellipse) and to closely attain the CRB shown as a reference (black dashed contour).

fading and interference: it thus guarantees high reliability and a reasonable level of determinism during communications, being this a crucial requirement for real-time control applications. As depicted in the corresponding histograms in Fig. 2-(b), the 95-th percentile latency is below 180 ms in all cases, considering relatively short (3 hops) to long hopping sequences (6 hops). Notice that, for proper actuation/configuration actions, the desirable communication latency is 250 ms or below. The maximum publishing latency can be scaled down from 6 up to 10 times compared to current industrial solutions.

III. Distributed Signal and Information Processing

Data processing is essential in the IoT architecture to extract application relevant information from the sensed data. Low latency applications, such as process control in IIoT [9] and road safety [18], [24], call for decentralized solutions where sensing nodes manage the computing tasks locally by cooperating to self disclose the information without sending the data to a remote unit. In this section, we focus on consensus-based methods [22], [23] for distributed inference exploiting the cloud-assisted IoT platform in Fig. 2. Consensus methods are used within the WCN for distributed estimation of application-relevant parameters by successive refinements of local estimates at individual nodes.

A. Consensus-based Algorithms for Distributed Processing

Consider a set of K nodes, distributed over a given area (as in Fig. 3-(a)), which have to cooperatively estimate p unknown real-valued parameters, $\boldsymbol{\theta} = [\theta_1 \cdots \theta_p]^{\mathrm{T}}$. In consensus-based algorithms, the estimate of the parameters of interest $\hat{\boldsymbol{\theta}}$ is computed at each node k, with $k = 1, \ldots, K$, by successive refinements of the local estimate $\hat{\boldsymbol{\theta}}_k(q)$ based on data exchange with neighbors through iterations $q = 1, 2, \ldots$, until a consensus is reached within the network, *i.e.,* $\hat{\boldsymbol{\theta}}_k(\infty) \to \hat{\boldsymbol{\theta}}$, as shown in Fig. 3-(b). A weighted-consensus approach is considered, where the estimate at node k is updated at iteration q as [22]:

$$\hat{\boldsymbol{\theta}}_k(q+1) = \hat{\boldsymbol{\theta}}_k(q) + \varepsilon \mathbf{W}_k \sum_{i \in \mathcal{N}_k} \left(\hat{\boldsymbol{\theta}}_i(q) - \hat{\boldsymbol{\theta}}_k(q) \right), \tag{1}$$

with $\mathcal{N}_k$ denoting the set of neighbors for node k, $\mathbf{W}_k$ a positive-definite weighting matrix and ε a step-size parameter. The estimate (1) is known to converge to the weighted average $\hat{\boldsymbol{\theta}}_k(\infty) = \left(\sum_{j=1}^K \mathbf{W}_j^{-1}\right)^{-1} \sum_{k=1}^K \mathbf{W}_k^{-1} \hat{\boldsymbol{\theta}}_k(0)$ of the initial estimates, provided that ε is selected to guarantee convergence [22]. In the conventional average consensus method [23], the weighting matrix is set $\forall k$ to $\mathbf{W}_k = \mathbf{I}_p$, with $\mathbf{I}_p$ being the p-dimensional identity matrix, so that the estimate converges to the arithmetic average of the local estimates, $\hat{\boldsymbol{\theta}}_k(\infty) = \frac{1}{K} \sum_{k=1}^K \hat{\boldsymbol{\theta}}_k(0)$. On the other hand, if the weighting matrix is selected as $\mathbf{W}_k = \boldsymbol{\Gamma} \mathbf{C}_k$, being $\mathbf{C}_k$ the covariance of $\hat{\boldsymbol{\theta}}_k(0)$ and $\boldsymbol{\Gamma}$ a scaling matrix, the estimate convergences to the optimal (in the minimum-variance sense) centralized solution $\hat{\boldsymbol{\theta}}_k(\infty) = \left(\sum_{j=1}^K \mathbf{C}_j^{-1}\right)^{-1} \sum_{k=1}^K \mathbf{C}_k^{-1} \hat{\boldsymbol{\theta}}_k(0)$, with minimal inter-node signaling (see [22] for details). Note that the conventional approach is suboptimal with respect to the weighted consensus method as it does not account for the different accuracies of the local estimates at different nodes.

Consensus methodologies are used in the following sections as basis to develop distributed algorithms for self-organization of cloud-assisted IoT networks, especially for passive radio sensing for positioning and people occupancy detection (see Sect. IV)

IV. Distributed Radio Sensing for Localization and Vision Reconstruction

Localization and vision technologies are expected to play a key role in next generation of cyber-physical systems. In the specific field of IIoT applications, tight integration of physical (*e.g.,* robots, automation and production systems) and software components (*e.g.,* control, monitoring, failure prediction, human-machine interfaces - HMI - applications) is made more complex by the interactions and collaborations with human workers.

In what follows first, we show a simple example of consensus-based network localization in indoor scenario, next device free localization scenario is explained and implemented using consensus-based radio sensing in cloud.

Fig. 4 shows an example of consensus-based network localization for an indoor IoT scenario with 17 IEEE 802.15.4

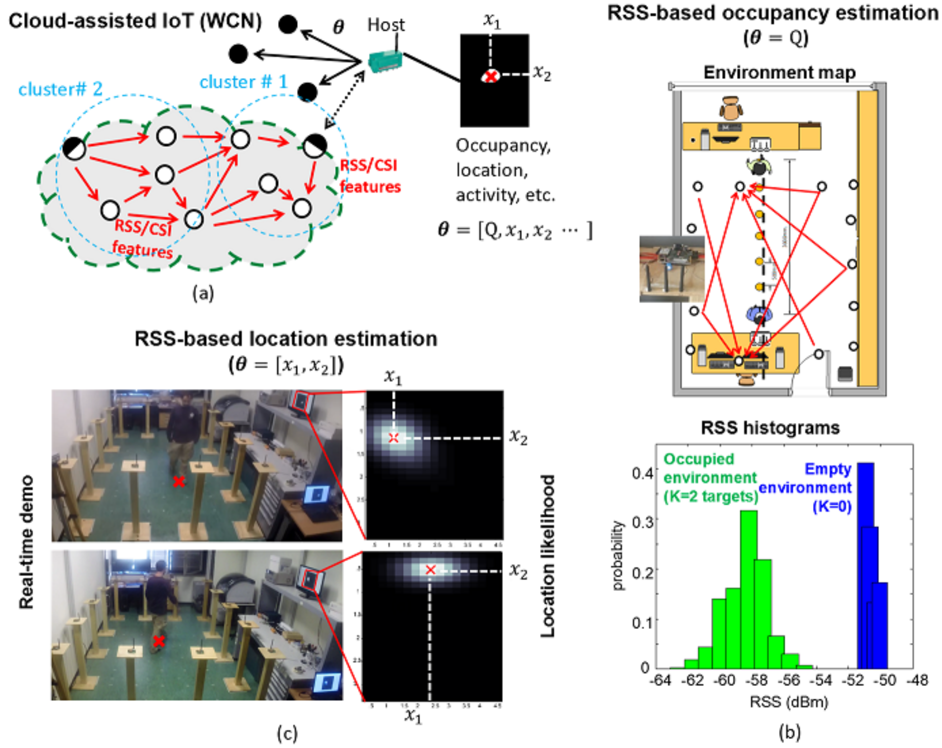

Fig. 5. (a) Cloud-assisted distributed estimation of user location or occupancy based on RSSI features exchanged among CNs, (b) device-free occupancy estimation using a network of 14 CNs (top) and RSSI histograms from individual CNs (bottom), (c) device-free location estimation using a network of 14 CNs (left) to compute the likelihood maps (right).

compliant nodes, including 8 anchors acting as reference nodes and 9 devices to be cooperatively localized from D2D received signal strength (RSS) measurements. The weighted-consensus algorithm is here used to enable each device to acquire the whole network topology, by successive refinements of local position estimates and repeated D2D interactions. In the figure, the average location accuracy is represented in terms of error ellipse at 39% level confidence. The proposed consensus-based method (*i.e.,* orange ellipses) is shown to significantly improve the conventional approach (*i.e.,* light blue ellipses) and to closely attain the CRB shown as a reference (*i.e.,* black dashed contour lines).

Device free localization (DFL) exploits RF signals exchanged between CNs to sense, detect and monitor alterations of the propagation environment that are induced by people or objects moving inside the WCN area. These methods allow the device-free human body motion recognition where the target does not carry any electronic device. These techniques rely solely on the acquisition and processing of the same electromagnetic (EM) fields propagated for the WCN connectivity. Body-induced alterations of the EM field, that covers the monitored area, are measured and processed in real-time by the CNs to extract information about the subject (*e.g.,* presence, position, or activity) or compute an image of the environment that originated the EM perturbation. RF device-free techniques have the advantage of not requiring any wearable devices, which in most industrial environments are largely unfit, and of being used also in presence of fumes, vapours and occluding materials.

DFL can be applied in industrial workspaces to track and protect operators, and to support safety, particularly in shared human-machine workspace [21]. As shown in Fig. 5-(a), each CN collects channel quality information (CQI) from the physical layer, such as the channel state information (CSI), or upper layers, such as the RSS, and sends such information to the CA nodes. For instance, focusing on RSS processing applications, the received power level (expressed in dBm) that is measured by a generic CN can be expressed as $P(\boldsymbol{\theta}) = P_0 - A_T(\boldsymbol{\theta}) + w$ where P_0 is the deterministic path-loss term that depends only on the geometry and the propagation characteristics of the empty scenarios (*i.e.,* the environment without any target inside), while the Gaussian random variable w includes the lognormal terms due to both multipath and measurement disturbances. The extra attenuation term $A_T(\boldsymbol{\theta})$ is due to the body-induced effects with respect to the empty scenario. According to the EM framework shown in [19], $A_T(\boldsymbol{\theta})$ can be modeled in terms of the monitored parameters $\boldsymbol{\theta}$ such as the target size and position, the link geometry and the small movements of the targets. This model can be also used to derive closed-form fundamental limits to DFL accuracy [20], thus providing an analytical method for DFL system design, calibration and network 2-D pre-deployment assessment.

Cloud devices act as virtual sensors, as they communicate with neighbors to fuse, process CQI data locally and perform low-level decisions on the sensed parameters $\boldsymbol{\theta}$. For example, occupancy detection is a low level sensing task where $\boldsymbol{\theta}$ represents the spatial density of parameters that is inferred by processing RSS measured over different sub-channels and links. CNs independently extract and evaluate features from RSS data to highlight any anomalous alteration of the EM field as possibly induced by body presence. These features can be defined in terms of extra attenuation, mean, likelihood, and spatial/frequency correlations of the received RF signals. Detected features indicating potential anomalies in the RSS field are then shared with neighbor CNs, while a consensus algorithm (Sect. III) is used to reach a decision about body presence. This information can be then used by the cloud for high level sensing tasks such as device-free positioning (where $\boldsymbol{\theta}$ represents the targets' locations), number of targets (for $\boldsymbol{\theta} = Q$) or activity recognition (with $\boldsymbol{\theta}$ denoting the type of activity).

Fig. 5 shows the experimental layout for occupancy detection in an indoor environment with two targets. In Fig. 5-(b) the RSS histograms highlight the body-induced perturbations of the radio signal strength observed by a CN, compared with the empty environment, where no target is inside the monitored area. Targets are moving along the line-of-sight (LOS) path. As shown in the figure, RSS values are sensitive to the presence of the subject in the surroundings of the CN, thus making detection of the occupied environment possible through RSS data inspection. In Fig. 5-(c), the localization of the subject is obtained by distributed fusion of RSS features computed by different CNs. Localization can be implemented based on the consensus approach. It shows the WCN used for tests that consists of 14 cloud devices. Consensus is here based on distributed fusion of local log-likelihood information obtained by individual CNs. The location likelihood maps obtained by the consensus procedure are plotted in Fig. 5-(c) on the right, where the target location $\boldsymbol{\theta} = [x_1, x_2]^{\mathrm{T}}$ is estimated according to the maximum likelihood criterion [21].

V. Concluding remarks

In this paper, we described a novel platform, referred to as wireless cloud network (WCN), that can lease advanced communication and sensing services to off-the-shelf IoT wireless devices via a dense network of self-organizing wireless nodes. The WCN paradigm is underpinned by distributed signal processing and offers the potential for improved reliability, connectivity and latency compared with current IoT solutions. An experimental case study for Cloud-IoT based device-free radio sensing considered for subject tracking. Future work will consider the applicability of the proposed platform in emerging high-frequency radio networks, ranging from the 60 GHz to the sub-THz bands (100-150 GHz).

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