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Internet of radar things for cognitive robotics

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ABSTRACT

Adapting Radar into industry become popular due to the enhancement of computational and communication systems. Industry 4.0 opens the door to use 5G connection to provide effective communication between things in the industry-the concept of combining industry 4.0 and radar sensors to exceed the conventional radar application. The idea of this paper is to propose a novel scheme to connect radar into one network to be an internet of radar Things (IoRT). In this scheme, we will allow radars to communicate as one sensor that processes the data sequentially to support the right decision to be made by robotics, especially when the radar sensor is mounted in robotics. Experimental data are presented to validate the process.

1. Introduction

The Internet of Robotic Things (IoRT) is a relatively novel field of study that was first introduced by ABI Research. Many scholars consider the IoRT to represent the advancement of the Internet of Things (IoT) on the basis which it incorporates active sensorization into the underlying technologies. It is anticipated that the IoRT will deliver significant opportunities for robotics entrepreneurs; however, it will not be without its challenges.

Razafimandimby et al. (2016) were concerned with two challenges in particular: Maintaining connectivity and collective coverage between multiple IoRT participants, and the development of a network control scheme by which it is possible to preserve global connectivity between various mobile robots to achieve the required service quality level. Furthermore, the framework proposed of this study aims to achieve a trade-off between delivering collective coverage while ensuring that the quality of the communication is sufficient. The IoT-based model involves computing the algebraic connectivity in combination with the utilization of the virtual force algorithm. As a result, the neural network regulator is fully disseminated and accurately replicates the IoT-based approach.

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There is an inherent need to perform a more systematic assessment in combination with theoretical analysis to support the development of teleoperation using an Internet-based robotic system. The interface between the human and robotics has been achieved using a standard network. A remote operator can use a web browser to control the navigation of a mobile robot in a laboratory setting. This interface provides a means by which the operator can access visual feedback and a simulated environment map to control the robot and achieved the desired tasks. While the system is in the early stages of development, it has the potential to be further enhanced for application within a range of real-world contexts; for example, teleservices, tele-manufacturing, and tele training (Hu et al., 2001).

Previous studies have investigated the architecture, underlying concepts, and primary characteristics and challenges of the IoRT. The primary objective of the current study is to generate a better understanding of the fundamental architectural design challenges associated with the IoRT, validate the intended concept, and identify further research directions that can facilitate the ongoing development of these groundbreaking technologies (Ray, 2016).

Kadir et al. (2012) described the use of an HTML-based webserver to develop a user interface that an operator can use to control a robotic arm via the Internet.

An engineered robotic laser ablation fitted with tweezers and a microscope was designed that operators can access and control online via a range of devices; for example, smartphones, desktops, and laptops. The system incorporates three distinct features: The mechanism for a user to operate the system from any device that can be connected to the Internet, the capability the image, ablate, and/or trap cells and their organelles via a "remote-control," and the flexibility to access and interact with the system in the lab using a personal computer without the requirement to be connected to the host machine (Botvinick and Berns, 2005).

An in-depth review of the main concepts that underpin the IoRT, the technologies and architecture involved, and the applications in which it is used, as described in Vermesan and Bacquet (2017). It also provides insights into the challenges associated with these technologies. The IoRT presents new convergence challenges that need to be taken into consideration in future developments. Specifically, there is a need to balance the need to achieve communication between multiple heterogeneous devices while also ensuring security and safety. The ongoing developments in parallel processing/communication between IoT heterogeneous and dynamic systems that employ concurrency and parallelism depend on new visions for incorporating intelligent technologies, collaborative robots (COBOTS) within IoT applications. Several factors are of significant importance when so-called cognitive devices become active participants within IoT devices. These include self-healing, dynamic maintainability, self-repair of resources, shifting resource state, (re-) configuration, and context-based IoT systems to implement and integrate services.

Jia and Takase (2002) described the development of an Internet-based robotic system that employs Common Object Request Broker Architecture (CORBA) to secure networking connections between a remote robotic system and a client. The client can transparently invoke a process on a server that is connected to the network without the requirement to know where the application servers are physically located and/or the underlying programming language.

Batth et al. (2018) provided an in-depth overview of the application of IoT technologies within the emerging IoRT applications. IoRT is a combination of varied technologies, such as artificial intelligence, cloud computing, machine learning, and the Internet of Things (IoT). The paper also considers the underlying architecture that plays a considerable role in the design of Multi-Role Robotic Systems for IoRT applications. Furthermore, it extends the discussion to consider the technologies that support IoRT, the potential applications of the IoRT, and the current robotic technologies based on a mobile, humanoid, swarm, and flying systems. It is anticipated that this paper will provide a strong starting point from which researchers can better understand the intricacies of the IoRT and develop new, cutting-edge applications that have real-world benefits.

The Internet of Things (IoT) permits an enormous quantity of "things," all with their unique addresses, to join in communication and data transfers using pre-existing Internet/network protocols. The concept of the IoT is not new. The concept was first outlined in an article related to ubiquitous computing in Scientific American entitled "The Computer for the 21st Century". The term itself was coined in 1999 by Kevin Ashton, at that time executive director of the Auto-ID Center. Further detail of the IoT as being a combination of people, processes, devices, technology, actuators, and sensors was introduced by Giusto et al. (2010). Furthermore, IoT offers a range of sensor technologies and data analysis techniques that can provide robotics with better information, a more comprehensive view, and more extensive information. However, unlike on-board robotics, it isn't possible to position IoT sensors in a flexible manner that facilitates the achievement of more active sensing approaches. The concept of link multiple sensors is known as wireless sensors network (WSN), which was used to operate smart antenna in order to increase the efficiency of performance and energy consumption (Fong, 2017; Salahuddin, 2015; Skiani et al., 2012). The WSN was studied to work for different mediums and environments such as underground applications and oil and gas monitoring. The passive radar is working the concept of receiving signals from multiple radiation sources (Baker and Hume, 2003; Falcone and La, 2012; Malanowski and Kulpa, 2012; Olivadese et al., 2013; Pastina et al., 2010; Qiu et al., 2013; Tan et al., 2005). Controlling and monitoring activities at automated industrial locations and deployment sites using radar sensors, allowing intelligent things to carry out monitoring of events on the periphery, process data taken from sensors around the site. Employ locally shared "radar intelligence" or "Cognitive radar" for the determination of the correct course of action, and then take action for controlling or disseminating radar elements in the real world seamlessly through the provision of a way of employing them as part of the Internet of radar Things (IoRT) (Ding et al., 2018; Metcalf et al., 2015; Rawat et al., 2016; Wu et al., 2014). To function robotics at an optimal level in terms of perception ability, robotics need to update environmental models and, thereby, acquire an understanding of their position (Bailey and Durrant-Whyte, 2006; Durrant-Whyte and Bailey, 2006). However, despite the significant advancements that have been observed in this regard, self-localization remains a major challenge, especially when robots are operating in indoor environments that do not have access to GPS or crowded settings, especially if there is a requirement for a high degree of reliability. RFID has been effectively harnessed to generate information that can help generate location data is one of the radio applications integrated to identify and localize objects for the internet of things (Gao et al., 2007; Michael and Darianian, 2008; Wu et al., 2012). Alternative methods include range-based techniques that are based on signals that are produced by remotely located infrastructure; for instance, ZigBee, visible light, Wi-Fi access points, or UltraWideband (UWB). (He and Chan, 2016;

Larranaga et al., 2010; Uradzinski et al., 2017; Zafari et al., 2019; Zhuang et al., 2018). While we can see progress advancing in systems employing multistatic radar techniques combining with other sensors as a sensor fusion system (Khan et al., 2017).

By integrating the IoT with human beings to communicate, collaborate, and analyze, real-time decision-making based on data is enabled. A central element of the concept is the fact that human beings are now surrounded within society by numerous smart objects that can be activated by actuators, sensors, radio tags, unique address protocols, secure communications, and standard architectural frameworks that allow for interactions and works with nearby devices to attain particular aims (Fiorini et al., 2018). A dynamic global network is described in Manzi et al. (2018) as IoT configurated to share slandered communication protocols. In which both virtual and physical elements are given physical attributes, identities, and personalities, employing smart interfaces, working together as part of a comprehensive network of information, frequently sharing data from users and their surroundings. We took the IoT vision into new advanced radar sensing, communication, and processing.

Linking multiple radars is knowing as bistatic/multistatic radar mode where the transmitter and the receiver in separate locations (Almutiry et al., 2017; Griffiths and Baker, 2006; Monte et al., 2010b; Wicks, 2007). By multistatic radar mode, the radar application exceeded some of its physical limitations. By noticing the multistatic radar, the process is done simultaneously. On the other hand, Tomographic radar exploits the degree of freedom of the geomatic diversity, which allows the radar to collect data from multiple locations using one antenna or more. Furthermore, the data of radar need a new scheme to take advantage of the processing, communication, and storage power of today's data centers that are linked to the cloud, making custom middleware platforms more independent, extra power demands, etc., which can limit the mobility of radars, their operating times, and raise operating expenses. Using the rates for cloud data transfer for offloading tasks when time is not of the essence is a significant cost reducer. The concept of IoRT can cover a distributed scheme operating in the cloud and at the edge. Moreover, IoRT can be used to access data about the features of a given object, including those directly observed by the sensors placed on robotics, and do have consequences for a robotics ability to grasp an object by obtaining the information contain data about the grasping points, size, shape of those objects, and amount of liquid that is in a vessel. IoRT will be employed to help the robotics locate items that were positioned in smart factories or in various areas of a lab. They were also used to pinpoint the position of the robotics within a given environment. This research presents a novel concept of IoRT assisting the robotics movement by increasing the connectivity between sensors. The IoRT will open a further period of adapting IoT and radars for industry solution providers. Thus, we can offer a definition of IoRT by combining definitions of network radars and IoT to represent a global framework for sharing information allowing cutting-edge radar performance through the interconnection of radar things via extant and evolving communication/information technology employing 5G, cloud computing, and other current Internet technology that employs an integrated cloud infrastructure/joint services allowing robotics to take advantage of the power of computing, communicating, and storing data in data centers linked to clouds, excising maintenance and update costs, making custom cloud-based middleware platforms more independent, and reducing power demands to increase mobility and operating times for radars.

To sum up, IoRT is founded in the cloud radar paradigm, employing some elements of cloud computing, e.g., technology for virtualization, and a trio of service models (software/platform/infrastructure), at the same time employing the IoT and enabling technology for creating significant scope for the design and implementation of novel applications for networked radars with the aim of providing shared computer resources as an essential element. Thus, it offers unique advantages but also creates particular challenges in terms of realization. The chief reason that there is a variety of definitions, viewpoints, and understandings of IoT is that this is not a novel concept per se. IoT is a new way of representing a type of business model that combines different technologies to have an interconnected and integrated business. The majority of techniques employed by IoT, e.g., heterogeneity and device identification, have not been newly invented. Instead, IoT adopts and adapts such technology to meet society's requirements for information technology in the political, social, technological, and economic spheres.

2. IoRT cognitive

Through a process of inference based on experience, cognitive robotics can develop a comprehension of where they are positioned within a location relative to other objects and to subsequently evaluate what implications the actions they take may have. This section will present a more in-depth overview of the performance of learning and reasoning tasks in a multi-actor IoRT setting. Knowledge models represent a significant aspect of cognitive technologies. Ontologies are important within IoT technologies because they facilitate the development of structured knowledge. Examples of ontologies that have a role to play in robots' ability to distinguish environmental factors are IEEE ontologies Robotics and Automation, and IoT (Prestes et al., 2013; Schlenoff et al., 2012). For instance, it exploited the ontologies Robotics and Automation ontology to achieve spatial reasoning between a set of robots that needed to coordinate with one another to deliver a missing tool to a human subject (Jorge et al., 2015). Alternative studies have used the cloud to extract information from a range of multi-modal data resources, for example, natural language. This is subsequently employed to generate a virtual environment in which robotics control policies can be simulated. In an IoRT setting, additional data sources can be incorporated into these knowledge engines. Cognitive approaches have found increasing applications within IoT-based studies that aim to facilitate distributed architecture management (Wu et al., 2014). In these studies, a self-organized set of analytics models are employed by the system in combination with a set of distributed sensor nodes and other tools. However, to the best of our understanding, researchers have yet to include robotics in these pipelines. One issue concerned with approaches that involve robotics supporting themselves as independent actors within a given content is that they possess more significant autonomy than the more conventional "smart" objectives that are used in the IoT. As such, they have more ability to change the environment, and this can have significant consequences. However, system adaptability concerns the extent to which it can change in response to various scenarios, contexts, and conditions. It includes the system's ability to respond to unanticipated events, evolving duties, and behaviors that were not previously expected. The configuration, perception, and decisional abilities outlined above are fundamental to achieving adaptability. As such, it is now worth examining the relevant platforms and application domains that can facilitate adaptability. The robotics that performs mobile functions need to have the ability to react to changes such as in crop sizes, weather conditions, light availability, field patterns, etc. (Fue et al., 2020). Finally, we exploit enablers between the radar sensors, robotics, and IoT to shape the support of cognitive robotics (Fig. 1).

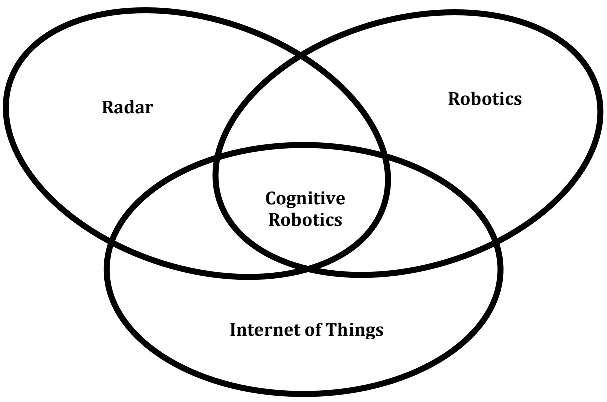

Fig. 1: The interference between the radar, robotics, and IoT fields

3. Mathematical model

RF tomography has promised technique in terms of generating 3D images of an object. Imaging the object allows us to detect more sensing features that can improve the industrial robotics operations based on IoT. The geometry diversity of the transmitters and the receivers caused by the robotics movements, which are located circulative diffused over the surveillance area, increased the resolution of the image and the depth of the detecting. However, a number of the transmitters and receivers, in this case, transmitters and receivers, have equal angular spacing in order to increase the scattered field value to obtain more information about robot status. A single transmitter operates at a certain location on the robotics movement space, for every single transmitter radiates a unique known waveform using a suitable polarization, a particular receiver activated in a certain location that is located to avoid forward scattering and the shadow of the object. The data collected when transmitting and receive in a different location due to the robotic movement we call it snapshot signal. In detail, the number of snapshot receivers and transmitters gives us an independent look-angle on the target.

Consequently, the information obtained for every single receiver is stored after processing and removing the noise and the clutter. The data collected will be transfer through the IP protocol to the main computer. We consider the beam width angle of the main lobe of the active transmitter antenna in the selection of the active receiver antennas. The inverse scattering problem was used to give us the advantage of reconstructing an image of the object. However, the expression of the scattered field to the object was derived by using the wave equation and the born approximation, and this relationship will be involved for geometry measurement to give an estimate of the object as a function of the scattered field.

The principle of inverse scattering to process data was collected by multiple receivers and transmitter snapshot signals (data capture). The number of receiver and transmitter snapshots gives us an independent look-angle on the target. The number of transmitter snapshot provided by N and each transmitter given position at r_n^a, the number of receiver snapshot given by M and given the position at r_m^a. Furthermore, the channels C can be fed separately where the angular frequency ω is driving the channel of each transmitter, which can be, represent as phase $d_{n,c}$ in the real and imaginary domain as the following:

$$\mathbf{d}_n = \left[d_{n,1}\; d_{n,2} \dots d_{n,C}\right]^T \quad (1)$$

where n is the number of the transmitter. The electric field of a certain number of activated transmitters S that have index set Γ_S at particular position $\mathbf{r}$ can be expressed as (Monte et al., 2010a):

$$E(\mathbf{r}) = \sum_{n\,\epsilon\Gamma_s} \sum_{c=1}^{C} \sum_{p=1}^{P} j\omega\mu_o l d_{n,c}\, \underline{\mathbf{G}}(\mathbf{r}.\mathbf{r}_n^a).\hat{\mathbf{a}}_{n,c} \quad (2)$$

which can be expressed as:

$$e(r) = j\omega\mu_0 l \sum_{n\in\Gamma_S} \underline{\boldsymbol{g}}(\boldsymbol{r}, \boldsymbol{r}_n^a) \cdot \underline{\boldsymbol{r}}_n^a \cdot \boldsymbol{d}_n \quad (3)$$

where $\underline{G}(r.r_n^a)$ is the dyadic Green's function. Under Born approximation assumption of the deriving a linear forward model, the total field received at n-position due to simultaneously transmitter m-th position can be expressed as follows:

$$E(r_m^b.\Psi) = \overbrace{Q\left[\hat{b}_m^T \sum_{n\,\epsilon\Gamma_s} \underline{\mathbf{G}}(\mathbf{r}_m^a.\mathbf{r}_n^a)\, \underline{R}_n^a\right]}^{Direct\ Path} +$$
$$\overbrace{Qk_0^2 \int_D V(r')\hat{b}_m^T \underline{\mathbf{G}}(\mathbf{r}_m^a.\mathbf{r}') \sum_{n\,\epsilon\Gamma_s} \underline{\mathbf{G}}(\mathbf{r}'.\mathbf{r}_n^a)\, \underline{R}_n^a \mathbf{d}_n d\mathbf{r}'}^{Scattered\ Field\ from\ Targets(First-order\ Born\ Approximation)} \quad (4)$$

$$Q = j2\pi f \mu_o l.k_o = 2\pi f\sqrt{\mu_o \varepsilon_o}\ \Psi = \{\mathbf{r}_n^a\}\ \forall\, n\,\epsilon\,\Gamma_S \quad (5)$$

The location of transmitting and receiving snapshot signal $\mathbf{R}_{n,m}^a$ is given by:

$$\underline{r}_{n,m}^a = \sum_{c=1}^{C}\left[(\hat{\boldsymbol{a}}_{n,m,c}\cdot\hat{x})\hat{x} + (\hat{\boldsymbol{a}}_{n,m,c}\cdot\hat{y})\hat{y} + (\hat{\boldsymbol{a}}_{n,m,c}\cdot\hat{z})\hat{z}\right] \quad (6)$$

The object profile at the measurement domain is given by:

$$V(r') = \varepsilon_r(r') - \varepsilon_D + j(\sigma(r') - \sigma_D)/(2\pi f \varepsilon_0) \quad (7)$$

where, D is the measurement domain, ε_D and σ_D are permittivity and conductivity. The location of the object is given by analyzing the environment of the measurement domain. The object profile V can be formed in a matrix L where the forward model can be expressed as:

$$v \cong \underline{L}^{-1}\cdot(e) \quad (8)$$

The inversion of the object profile v is obtained by conjugate gradient algorithm to solve the inverse problem as linear system equations.

4. Proposed algorithm

The purpose of the algorithm is to enhance the robotics awareness, increase the sensorization of robotics arms, and update the geo-location of the robotics with other hazard movement or walking workers. We achieved our goals of the proposed algorithm by the interactions between the robotics geo-location and the data collected based on the IoT. The algorithm flow chart started with the information obtained from the robotics arm operation system about the geo-location of the robotics arm, as shown in Fig. 2. The geo-location data is containing the xyz location beside the orientation of the antenna mounted on the robotics arms. The geo-location information of the sensors will be assigned for the scattering field collected from the sensors at a specific location and time for further processing. In order to create a matching filter, the electromagnetic field response of the scattering field is calculated through the Green's function to provide a dynamic impulse response matrix L. The Geo-location data collected before the robotics movement is used to determine the parameters of the Green's function. By processing the data from the scattering field E^S and electromagnetics response matrix as a linear system equation under the first-order Born approximation assumption to linearize the system. The object profile can be granted through solving an ill-posed system that needs to use the conjugate gradient algorithm to produce the solution. The information obtained after solving the linear system equation, such as the location of the target, its material, and orientation, will be stored and added into the measurement scene. If the robotics arm is moving, the algorithm will start collecting the geo-location, scattering field, and processing the data to obtain the measurement object profile and feed it into the robotics arm cognitive and awareness system that will analyze its location and movement through the process. The data can be stored, transferred, and processing in the cloud computing system is advantaging from the 5G network. The results in the next section are showing the connectivity of the multiple sensors based on the robotics arms movement observed by the output of the sensor processed data.

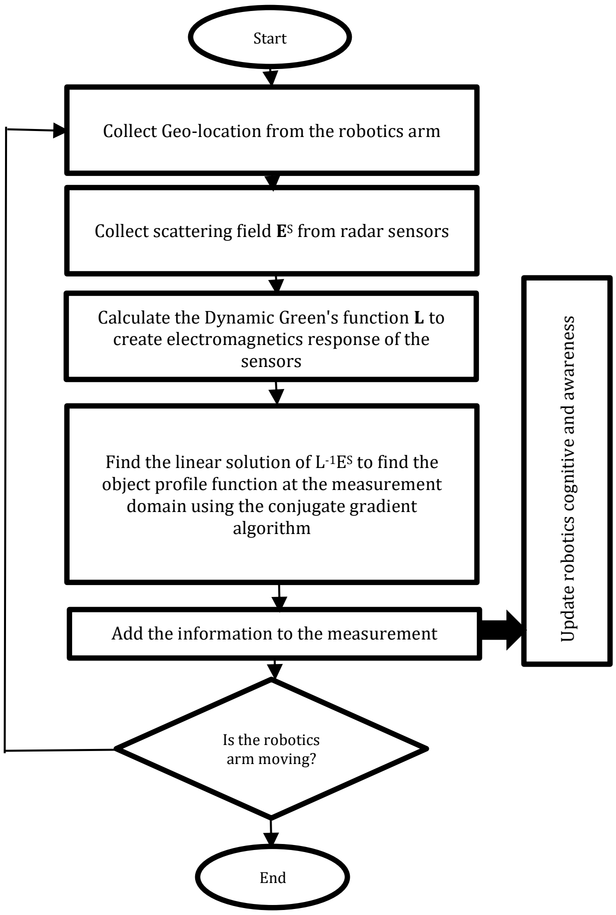

Fig. 2: The flowchart of the internet of radar things

5. Results and discussion

In this experiment, we used YASKAWA robotics arms to operate and move a radar antenna mounted at the end of the robotics arms, as shown in Fig. 3 where the distance and the antennas orientation of the robotics geometry are labeled in Fig. 3 to be matched with electrical field responses that are shown in Fig. 4. The six axes robotics arms can have a vertical reach up to 5615mm and a horizontal reach up to 3121mm with repeatability of about ±0.15mm. We used the RF lambda RCDLPHA2G18 antenna. We used a corner reflector to provide a baseline point as a hit target.

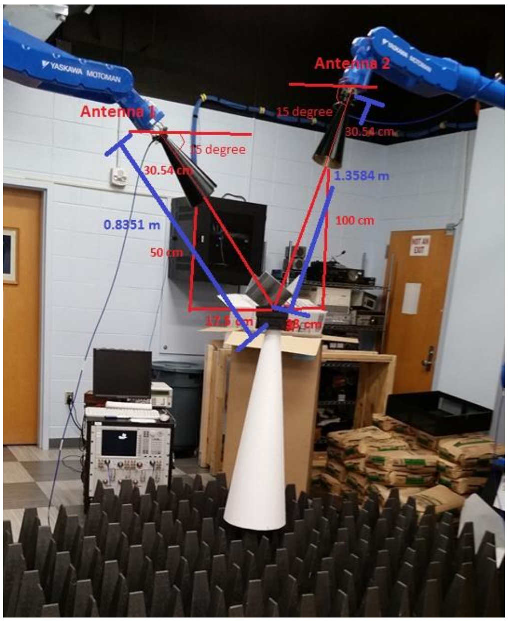

Fig. 3: The actual scene of the measurement with the distances between the object and the antenna

The X-band frequency operation Horn antenna provides two ways of information from monostatic and bistatic radar mode to compare the data. The data was sent by an IPv6 protocol that links the eight-port vector network analyzer VNA (Keysight N5221A PNA Network Analyzer) to communicate to the computer to store and process the data. We used Root Manager, which is a Windows PC-based solution for troubleshooting robot jobs and debugging issues in real-time provided from Yaskawa. Robot Manager communicates directly to the robot controller using high-speed Ethernet, providing the ability to view and edit robot jobs, I/Os, and variables that we connected to the radar imaging position data.

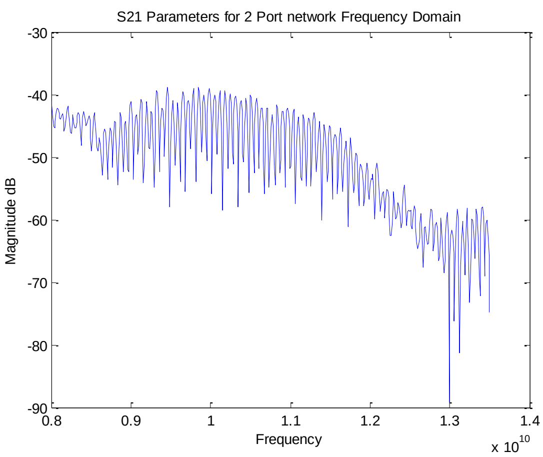

Fig. 4: The Electromagnetics response of the corner reflector at the frequency domain measured by the radar antenna

As part of the calibration procedure in the Mumma lab, we detect corner reflector at different modes, such as obtaining the corner reflector in the frequency domain, as shown in Fig. 4, then apply the same data for a test in the time domain as shown in Fig. 5.

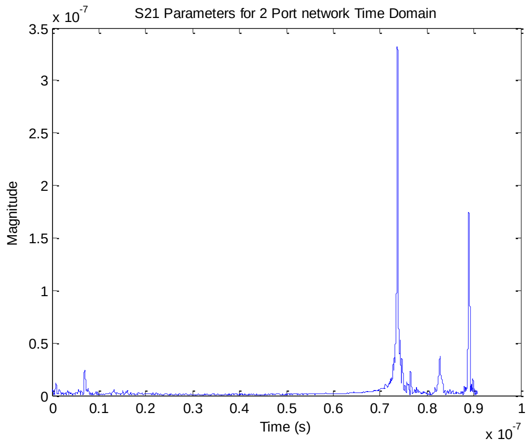

Fig. 5: The time-domain response of the corner reflector before calibration measured by the radar antenna

Measuring the data at a different domain will increase the accuracy of that data after we apply any further process to remove/reduce unwanted natural effects such as multipath and mutual coupling. Applying range gating, allowing us to process the object at a certain distance and neglect the far distant object or reflection, as shown in Fig. 6 as results of domain data investigation. Next, we had been moving the robotics arms to test the range gating techniques while collecting data is shown in Fig. 7. The range gating at different locations will provide accurate results of the gating purpose. Fig. 8 shows the absorbing materials eliminating unwinding re-election like floor/ceiling clutter.

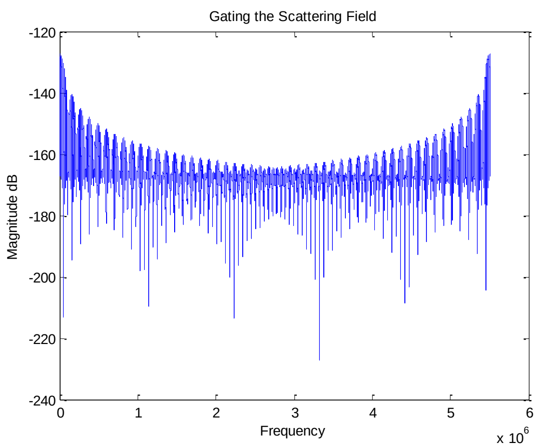

Fig. 6: Gating the scattering field shows the refection's at different frequency and magnitude

The absorbing material converts the unwanted reflected electromagnetic waves into thermal energy in order to attenuate it. However, there is a misalignment of about 8cm for each antenna between the actual distance and electromagnetics measurement. The electromagnetics measurement results in Fig. 9, Fig. 10, and Fig. 11, are shown how we detect the target using a network analyzer device, two robotics arms, two antennae, and a corner reflector to provide more information about the robotics arm location and orientation through update the Robot manager data. We measured S-parameters such as S21 for a bistatic mode, and there is misalignment about 24cm between the actual distance and the measurement, as shown in Fig. 9.

Fig. 7: Obtain the range of the corner reflector due to the radar antenna

Fig. 8: Absorbing material to suppress the floor reflection by converting electromagnetic field into thermal energy

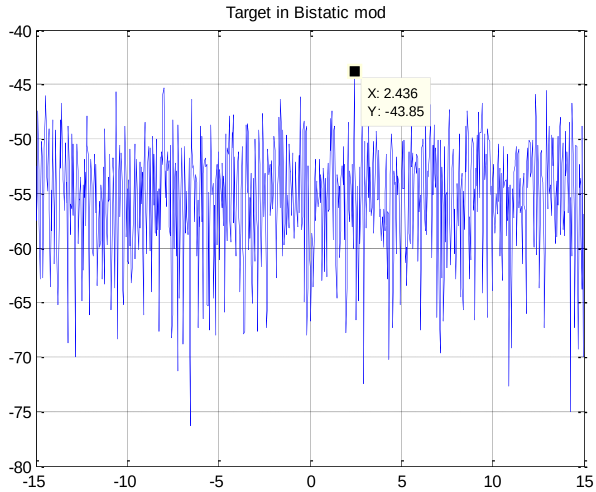

Fig. 9: The bistatic radar mode detecting the target at 2.1936m, but we find it at 2.436m

In this experiment, the accurate geo-location of the robotics arms and the object allows us to process the data as tomographic radar images that can provide information about the object location, the tomographic image inside the object, and analyze the object material and shape. Fig. 10 shows the monostatic mode of the measurement S-parameter S11 to match the results where it appears more accurate due to the antenna orientation.

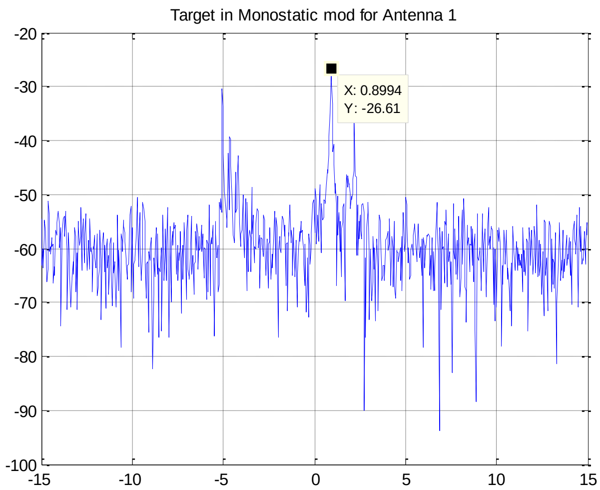

Fig. 10: The monostatic radar mode detecting the target by antenna 1 at the actual distance at 0.8351m, and it's found at 0.8994m

The corner reflector has a strong radar cross-section than other objects in the scene, including the clutter and multipath effects. For antenna 2 at the monostatic mode that is shown in Fig. 11, the corner reflector has appeared at 1.424m, where the target is located at 1.3584m. The mismatch of the actual value and the measured values of the distance is shown in Table 1. The first raw at the table is presenting the actual distance between the corner reflector and the two radars in bistatic mode. The actual distance is 2.1936m, where the measured value is 2.436m.

The distance mismatch is due to many reasons such as transmitter and receiver distortion, uncalibrated near-field measurement, microwave mismatch network component, etc. The monostatic radar mode has better performance due to the main-beam of the antenna. The first radar antenna as the monostatic mode is located at 0.899m from the corner reflector, where its measure at 0.8351m with less than 0.06m mismatching. The second radar antenna monostatic mode is located at 1.424m when the measurement shows the corner reflector at 1.358m with 0.066m mismatching. The corner reflector has appeared at the bistatic mode at -43.85 dB intensity, which considers low compere with noise at the scene. On the other hand, the monostatic is shown better performance in terms of reflected power.

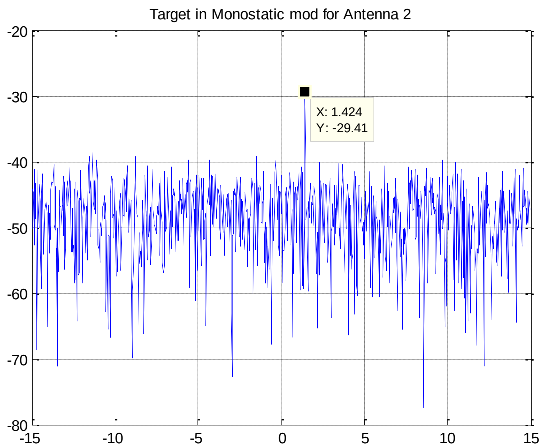

Fig. 11: The monostatic radar mode detecting the target by antenna 2 at 1.424m where the actual distance 1.3584m

Table 1: The corner reflector measurement

Radar	Actual (m)	Measured (m)	Target (dB)
Bistatic Radar Mode (shown in Fig. 9)	2.1936	2.436	-43.85
Monostatic Radar 1 (shown in Fig. 10)	0.8351	0.899	-25.65
Monostatic Radar 2 (shown in Fig. 11)	1.424	1.358	-29.41

6. Conclusion

This paper has put forward a proposed architecture that combines Radars with the IoT to create the Internet of Radars Things (IoRT) in order to develop the potential of cognitive robotics. The IoRT will permit radar systems to make connections, participate in sharing and dissemination of environmental information, contextual information, business activities, and computational resources, and to gain new information/skills that they have not previously been endowed with, under the aegis of complex architecture. This provides new potential in the connected radars field that we contend will be responsible for many exciting innovations in the future. It permits the adaption of the existing connected ecosystems, allowing various technology to leverage economic radar sensors to work with cloud services, a variety of devices, processes, and communication networks. We have put forward a new form of architecture for the IoRT that involves combining radars with the IoT. It has been demonstrated that the suggested architecture is viable by establishing the already existing or soon to exist key elements such as cloud-enabled radar platforms, IoT processes, and existing radar systems with the peripherals. A description has also been given the central elements of the system. The future contribution research would at the topic of combining the AI with radar data to support a robotic decision. The other issue would be merging the tomographic radar at the production line to offer real-time inspection.

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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