# Wireless Networks Featuring Twin Functionality for 6G Networks

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***Abstract:** With the progress of 5G standardization scholars speculate about what the sixth generation will bring. The incorporation of sensor technology is developing as a significant component of the sixth-generation Radio Access Network, enabling for the construction of an intelligent network using dense cell infrastructures. The study presents a thorough examination of the history, variety of major uses, and cutting-edge techniques of Integrated Sensing and Communications (ISAC). The paper begins by examining the historical interaction of sensing and communication, followed by an examination of the many components of ISAC as well as the ensuing improvements in performance. The authors provide insight into ISAC's advancements in industry and standardization operations by providing both present and anticipated case studies.*

***Keywords:** 6G networks, Additive white Gaussian noise, Communication, Integrated sensing, Null hypothesis, Perceptive mobile networks.*

## I. INTRODUCTION

6G wireless services are being considered critical facilitators for a wide range of future uses. Such uses need excellent wireless communication and very precise and robust sensor capabilities. A prevalent theme across many imaginative ideas regarding 6G wireless networks is the fact that perception will have a larger role than in the past [1]. The technical advancements readily indicate that humans are prepared to adopt novel sensory functions in the next sixth-generation era. In fact, radio sensing and communication (S&C) technologies are both advancing towards higher frequency bands, bigger antenna arrays, and downsizing, resulting in hardware designs, and channel features, including signal processing that have grown ever comparable. This presents an intriguing possibility for sensing to be implemented via radio services, whereby the next generation of networks will extend past traditional communication and enable universal sensing capabilities to gauge or even photograph surrounding areas. This sensing capability as well as the network's capability to gather sensory input from the surroundings is viewed as facilitators for developing and generating intellect for an upcoming smart world that might come into widespread uses like multiple location/environment-aware situations. Vehicle-to-everything, home automation, intelligent production, surveillance, ecological tracking, and communication between humans and computers are just a few examples that will be covered in the applications part [2]. The data handling for Sensing and Communication differs noticeably. Sensing gathers and retrieves data from noisy assessments, whereas communication is concerned with conveying information through specially-suited signals followed by retrieving the data from a noisy context. Integrated sensing and communication's ultimate objective is to integrate both of these tasks, while investigating immediate tradeoffs and shared performance benefits. In one scenario, ISAC is projected to significantly enhance spectrum and energy efficiency while reducing hardware plus transmission expenses, because it seeks to combine detection and connectivity into a single network that formerly struggled for various kinds of assets. ISAC, on the contrary, promotes a more comprehensive integration model in which the two capabilities are created together for mutual advantage, that is, through connectivity-assisted perceiving and sensing-assisted transmission [3]. ISAC is described as a design technique that merges sensing and communication features to promote optimal wireless utilization of resources and mutual gain [2]. Two prospective intelligence service gains can be extracted from the above definition:

1) Integration Gain: achieved by the shared utilization of wireless services for a pair of S&C objectives to eliminate repetition of transfers, components, as well as facilities.
2) Coordination Gain: achieved by collaborative support among S&C [2]. By predicting how ISAC is going to have a substantial part in 6G mobile networks, future wireless local area networks, including the V2X system, authors provide a summary of ISAC applications, use cases, technological methods, obstacles, and potential.

## II. LITERATURE REVIEW

Early ISAC implementations [4] incorporated communication data into a set of radar signals using pulse interval modulation. Radar's evolution, as a primary symbol for sensing methods, was strongly influenced by wireless networking, and inversely. Previous radar systems were powered by mechanical motors and searched for desired targets in space while moving their antenna(s) on a regular basis. These conventional radars have a number of serious issues, including an absence of multi-functionality along with adaptability, and also potentially simpler to trap and interfere with. As a result, the phased array, also known as the electronically-scanned arrays technology, was created to overcome several of such limitations [5]. Phased-array devices create spatial frames of signals that may be electrically directed in various orientations rather than manually rotating their antennas. During WWII, the German firm GEMA produced the first ever phased-array radar, the "Mammut," which was able to identify targets appearing at a height of 8 kilometers at a distance of 300 kilometers [6]. “Mammut” was the inspiration for the development of MIMO transmission systems which paved the way for the development of the 3G, 4G, and 5G digital eras [7], [8].

Massive MIMO, which eventually became one of the key solutions for 5G-and-beyond networks [10], was first suggested in Marzetta's foundational study in 2010 [9]. A seminal work on the viability of using millimeter wave transmissions for mobile communications was released in 2013 [11]. Later, mmWave and mMIMO worked flawlessly together for one another's benefit. The shorter signal wavelength allows for the physical reduction of massive MIMO antenna arrays, while the strong beam forming gain of the mMIMO array allows for the longer transmission distance of mmWave signals. The enormous expenditures on hardware in addition to power demands imposed by the several mMIMO mmWave systems, however, offer a significant obstacle to their widespread application.

As operational frequencies approximate the mmWave range, radar, & communication have a tendency to be comparable in terms of channel properties and signal processing methods [9]. Because the accessible propagation pathways in the sub-6 GHz range are minimal, the millimeter-wave communication pathway is limited and governed by Line of Sight (LoS). As a result, the millimeter wave channel model is more closely aligned to physical geometry, which has prompted the establishment of beam level signal processing techniques for communication over mmWave [1], [13]. Beam orientation, proximity, surveillance, as well as management of the beam are examples of approaches that can be built around a HAD framework [14]. It is worth mentioning that communications in the beam domain, to some extent, replicate traditional radar signal processing, wherein beam orientation and surveillance can be considered as target-seeking and tracking [15].

As a result, the line connecting radar and communication becomes hazy, as well as the capacity for sensing may not be restricted to the radar network. The technological underpinning and reasoning of ISAC [2] is that cellular networks and devices may conduct sensing through radio emission and communication. Sensory information may be gathered and used to improve communication efficiencies, such as sensing-aided vehicle beam shaping and managing resources. Furthermore, forthcoming wireless networks' integrated sensing capabilities open their "vision" to evolve into perceptive networking [16], [17]. Such networks constantly perceive their surroundings, delivering services like urban traffic tracking, meteorological perception, and human activity identification. The abundance of collected data serves as the foundation for developing intelligence for the ISAC network and upcoming home automation, transport, and municipal services.

## III. METHODOLOGY

### *A. Sensing Methodology*

Sensing operations are loosely grouped into three distinct groups: detection, estimation, and recognition, and are all performed according to gathered signals/data with regard to the perceived objects. [18].

1) **Detection:** provided noisy and interfering observations, detection implies to arriving at binary/multiple choices regarding the states of a detected item. These states often involve either the existence or the lack of a target along with the triggering of a happening, like tracking motion, which may be represented as binary data or multi-hypothesis assessment issues. Using the binary identification issue as a case study, researchers pick between the two possibilities H1 and H0 depending on the recorded signals, i.e., whether the object of interest is present or missing. Detection measures comprise detection probability, which can be described as the likelihood that H1 remains valid and the detector selects H1, while false-alarm probability, is described as the likelihood of H0 holding valid yet the detector selects H1 [19].

2) **Estimation:** Estimation is the extraction of meaningful characteristics from noisy and/or interfering observations of a sensed object. This may involve estimating the target’s

distance/velocity/angle/quantity/size. The mean square error as well as Cramér-Rao bound [20] may be employed to assess estimation performance. MSE is defined specifically as the average of the squared deviation between the actual worth of a parameter and its estimate. CRB is a lower constraint upon the variance generated by an unbiased estimator, which is defined as the Fisher Information. FI is the expected bending (with no positive second derivatives) of the probability distribution with respect to$\theta$, which gauges the estimator's "sharpness" or accuracy.

3) **Recognition:** Understanding what the perceived item represents depending on noise and/or disturbed perceptions is referred to as recognition. Target recognition & human activity or event recognition are examples of this. Recognition is commonly characterized as an application-layer classification job, the performance of which is measured using the recognition accuracy parameter. [21].

### B. *Communication methodology*

Communication activities may be divided into layers and assessed based on two criteria: efficiency and dependability.

1) **Efficiency:** The effective transmission of data comes at the expense of wireless resources like spectrum, space, and energy. As a result, efficiency is a parameter that assesses what amount of information is effectively conveyed through the transmitting device to the receiver in the face of restricted resource availability [22], [23]. Spectral efficiency in addition to energy efficiency is defined as the attainable speed per unit bandwidth/energy and is frequently used, with values of bits or Hertz and bits/channel usage and bit/s/Joule, respectively. Furthermore, channel bandwidths, coverage, as well as a large number of customers serviced are also critical efficiency measures.
2) **Dependability**: A communication system must be resistant to damaging elements in the communication pathway. In other words, we anticipate communication systems to function amid noise, interference, or fading. As a result, dependability assesses a communication system's capacity to decrease or even repair incorrect data bits [22], [23]. Downtime probabilities, bit error rate (BER), symbol error rate (SER), and frame error rate (FER) are all common measurements.

## IV. IMPLEMENTATION

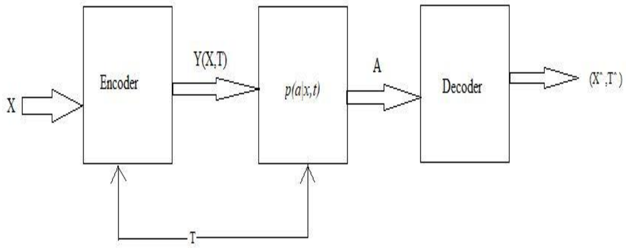

Figure 1: Information transmission over a state-dependent channel.

As indicated in Figure. 1, the sender intends to convey to the receiver simultaneously pure data, i.e., an index X ∈ {1, 2… $2^{nR}$ and a description T^ of the channel state T. The transmitter sends a code Y (X, T) to its recipient at a rate of R, provided the information indexes X & state T. The recipient notices

$$A \sim \Pi_{i=1}^{n} p((a_i|y_i, t_i) \qquad (1)$$

The information is subsequently decoded by the receiver from A as X^ (A) ∈ {1, 2.... $2^{nR}$}, and calculates the state as T^ (A). The probability of decoding mistakes and state estimate errors is stated as

$$P_e^{(n)} = \frac{1}{2^{nR}} \sum_{i=1}^{2^{nR}} P_r \{X\hat{} \neq \mathrm{i} | X = i\},$$

$$\mathrm{D = E\,\{d\,(T, T\hat{})\}}, \qquad (2)$$

Here d (T, T^) is a measure of distortion between T and T^. A rate-distortion combination (R, D) is said to be feasible if a series of ($2^{nR}$, n) codes Y (X, T), in such a way that [24]

$$\mathrm{E\,\{d\,(T, T\hat{})} \leq \mathrm{D}, P_e^{(n)} \rightarrow 0, \mathrm{n} \rightarrow \infty \qquad (3)$$

The estimate MSE may be given if the distortion function is selected as the squared state estimation error.

$$\mathrm{E\,\{d\,(T, T\hat{})} = \frac{1}{n}\ \mathrm{E}\|T - T\hat{}(\mathrm{A})\|^{\,2} \quad (4)$$

Using the metric described above for state estimation and the state-dependent Gaussian channel A = Y (X, T) +T+N, where $T_i$ ~ N (0, $Q_S$), $N_i$ ~ N (0, $Q_N$), .Consider the Pareto-optimal border of the (R, D) pair γ ∈ [0, 1] is [24]

$$(\mathrm{R, D}) = \left(\frac{1}{2}\log(1 + \frac{\gamma^P}{Q_N}\right), Q_S \frac{(\gamma^P + Q_N)}{(\sqrt{Q_S} + \sqrt{(1-\gamma)^2} + \gamma^P + Q_N}) \quad (5)$$

Here $\frac{1}{n} E\{\sum_{i=1}^{n} Y_i^2\ (X, T)\} \leq$ P is a power limitation on Y that is expected. It can be demonstrated that the aforementioned tradeoff is realized by the power-sharing technique, which divides transmit power into γP and (1 − γ) P, for conveying pure data and a channel state scaled signal, respectively [24]. To achieve the best tradeoff, the power resource is divided between pure information delivery and channel state estimation.

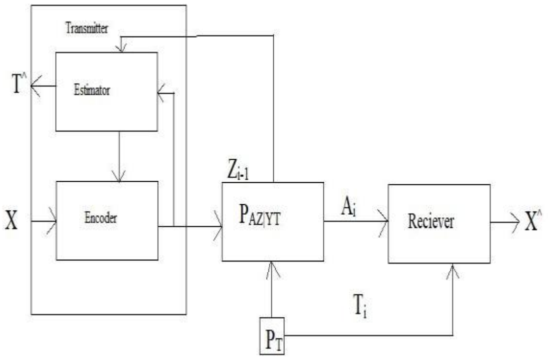

Figure 2: Mono-static ISAC channel

The aforementioned rate-distortion tradeoff does not account for target estimation via reflected echo. Indeed, with mono-static radar, the transmitter is unable to predict the state of the target channel in advance; otherwise, there would be no need to perceive the target. The channel's state is accessible to the receiver but unknown to the transmitter, as seen in Figure 2. The transmitting device uses an estimator to recreate the state estimate Tˆ for every broadcast through the uncertain feedback output $Z \in \mathbb{Z}$. The transmitter delivers a symbol $Y \epsilon \Upsilon$ using an encoding device depending on both X and Tˆ by selecting a message X. The channel sends $A \epsilon$ Å to the receiver and returns its state to the transmitting device. The TYAZT joint distribution may be stated as

$$P_{TYAZT^{\hat{}}}(t, y, a, z, t^{\hat{}}) = P_T(t)\, P_Y(y)\, P_{AZ|YT}(a, z| y, t)\, P_{T^{\hat{}}|YZ}(t^{\hat{}}| y, z) \quad (6)$$

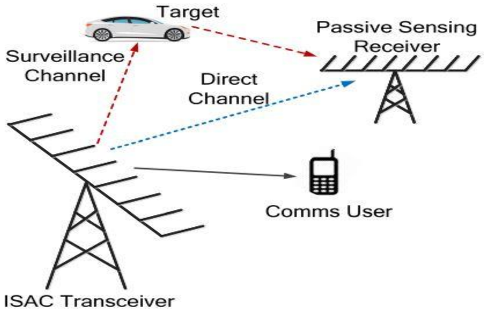

Figure 3: Joint passive sensing and communication

As illustrated in Fig. 3, an ISAC transmitting device uses a part of its total power budget to emit a sensing waveform $s_R$ (t) to identify targets and another portion to produce a signaling waveform $s_C$ (t). The two transmissions are planned across orthogonal (time-frequency) resources to avoid interference. The sensing receiver (SR) gets $s_R$ (t) via both the direct and surveillance channels and is looking for the existence of a target in the second channel. The communication user (CU), on the other hand, obtains $s_C$ (t), which includes useful data. The challenge then becomes allocating power to the S&C features in such a way that detection performance may be maximized while maintaining a low communication rate. This may be expressed as the optimization issue shown below.

$$\frac{max}{P_R, P_C} P_D \text{ s.t. } R \geq R_{th}, P_R + P_C = P_T \quad (7)$$

Where $P_R$ and $P_C$ denote the transmit power of radar as well as communication messages, respectively, and $P_T$ denotes the overall power budget. The radar's detection probability is denoted by $P_D$, and the attainable rate is R = log (1 + $P_C$ γc), where γc is a channel gain adjusted by the noise variance. Finally, Rth represents a rating barrier. The SR recognizes the object of concern in the surveillance channel in a passive radar system by associating the reflected signal with a reference signal obtained through the direct channel [25]. The detection issue may be described as the one that follows the binary hypothesis testing problem by sampling the incoming signals as L time domain samples:

$$\mathcal{H}_0 : \{ {}^{y_d = \gamma_d G_{d s_R} + n_d}_{y_s = n_s}$$

$$\mathcal{H}_1 : \{ {}^{y_d = \gamma_d G_{d s_R} + n_d}_{y_s = \gamma_s G_{s s_R} + n_s} \quad (8)$$

*where* $\mathcal{H}_0$ And $\mathcal{H}_1$ represent the hypotheses of target-absent as well as target present, respectively. $Y_d$ and $Y_s$ are actually the signals acquired from the direct and surveillance channels, respectively, and $G_d$ and $G_s$ represent the L x L single delay-Doppler operator matrix structures relating to the direct and surveillance channels, with γd and γs being the scalar coefficients of the two channels. Finally, $n_d$ and $n_s$ have variances of σ2 and are composed of AWGN. A generalized probability ratio test is used for detection and in situations when the direct-path SNR (D-SNR) is large, the associated PD may be estimated as

$$P_D \approx Q_1\left(\sqrt{\frac{2P_R|\gamma_d|^2}{\sigma^2}}, \sqrt{2_\gamma}\right), \quad (9)$$

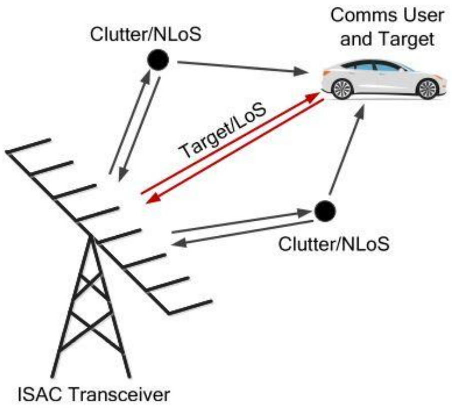

Figure 4: NLoS reduction

To improve communication performance in a general communication system, one must "exploit all the possible degrees of freedom (DoFs) within a channel" [23]. For instance, Non-LoS (NLoS) propagation, which causes channel fading, was once thought to be bad for wireless systems. Surprisingly, a general understanding that NLoS routes and fading effects may be used to create variation and DoFs for MIMO transmissions is condensed with the development of multi-antenna technology. Contrarily, not all pathways are helpful for sensing, and certain of them could have a detrimental effect on how well it works. Most of the time, sensing requires an explicit LoS route to exist between the sensor & the object being sensed. Signals received from elements apart from the targets of interest are called to as "clutter" in normal radar applications; they are deemed damaging and need mitigation. This group often includes NLoS components. So long as it provides information about the destination of interest, a particular propagation pathway can be valuable for both tasks. If not, this route is solely good for communication and detrimental to sensing. This illustrates the conflicting demands in S&C. Consider the straightforward example depicted in Fig. 4 in which an mmWave BS additionally serves like mono-static radar outfitted with Nt and Nr broadcast and receive antennas to further understand this.

The Nv-antenna vehicle is being served by the ISAC BS while being followed by it, indicating that it is dual, a CU as well as a target. ISAC signal matrix X $\in C^{N_tXL}$ is transmitted and the obtained output at the vehicle is represented by the

$$Y_C = a_0 b_v(\emptyset_0) a_t^H(\theta_0) + \sum_{i=1}^{I} a_i b_v(\emptyset_i) a_t^H(\theta_i) X + Z_C$$

$$\triangleq HX + Z_C \quad (10)$$

Where the ith path's angle of arrival (AoA), angle of departure (AoD), and channel coefficient, respectively, are denoted by $\varphi_i$, $\theta_i$, and $\alpha_i$. i = 0 and i ≥ 1 are the metrics of the LoS path followed by NLoS paths, at (θ) ∈ $C^{N_tXL}$and $b_v$ (φ) ∈ $C^{N_vXL}$ are the steering paths for the broadcast antenna array of the Base Station followed by the receiver antenna array of the automobile, respectively, and I is the overall number of accessible paths in the channel. Researchers ignore the time lag along with the Doppler of every path without losing generality, as you may have seen.

Considering that each NLoS route is a clutter source, the automobile's redirected echo is received by the ISAC BS as

$$Y_R = \underbrace{\beta_0 a_r(\theta_0) a_t^H(\theta_0) X}_{\text{Target}} + \underbrace{\sum_{i=1}^{I} \beta_i a_r(\theta_i) a_t^H(\theta_i) X}_{\text{Clutter}} + \underbrace{Z_R}_{\text{Noise}}$$

$$(11)$$

Here $a_r$ (θ) ∈ $C^{Nr\times1}$ is the steering vector for the receiver antenna array of the ISAC BS and $\beta_i$ being the reflection coefficient of the ith clutter. From (10), we can observe that the automobile's received SNR is provided by

$$\mathrm{SNR}_C = \frac{\|\mathbf{HX}\|_F^2}{L\sigma_C^2} \qquad (12)$$

Here overall propagation pathways add to the receiver power. SCNR of the targeted object received, on the other hand, is expressed as [124] from (11).

$$\mathrm{SCNR}_R = \frac{\|\beta_0 \mathbf{a}_r(\theta_0)\mathbf{a}_t^H(\theta_0)\mathbf{X}\|_F^2}{\|\sum_{i=1}^{I} \beta_i \mathbf{a}_r(\theta_i)\mathbf{a}_t^H(\theta_0)\mathbf{X}\|_F^2 + \sigma_R^2} \qquad (13)$$

To maintain S and C efficiency, an ISAC waveform X must be precisely built to distribute energy and various other resources to every propagation path, ensuring both S&C efficiency, while convex optimization methods may be used to tackle the problem. The foregoing tradeoff may be extended to general ISAC scenarios with numerous targets/CUs of concern, including parallel imaging and communications [26] if various pathways are deemed helpful for sensing.

### *A. Signal Processing ISAC Receiver*

The necessity to do S&C duties at the same time presents particular obstacles in the receiver handling of signals. An Integrated sensing receiver ought to be able to decode meaningful information from the transmission signal while also detecting/estimating targets from the echoes. As both S&C are interference-free, conventional signal processing may be used indefinitely if the two signals do not overlap. Mutual interference occurs, however, if the two signals are entirely or partially overlapped in both the time & frequency spectrums, and this is the cost of attaining the integration gain. In Fig. 5, we show a general ISAC receiver structure with combined communication as well as echo signals obtained from the specific antenna array and enhanced, down-converted, and processed from an RF chain. The sampled signals are then routed inside communication and sensing processor units to perform information decryption and object detection/estimation/recognition, with S&C cooperating to assist mutual interference cancellation. Within this paradigm, the next sections provide an overview of cutting-edge ISAC receiver signal processing algorithms.

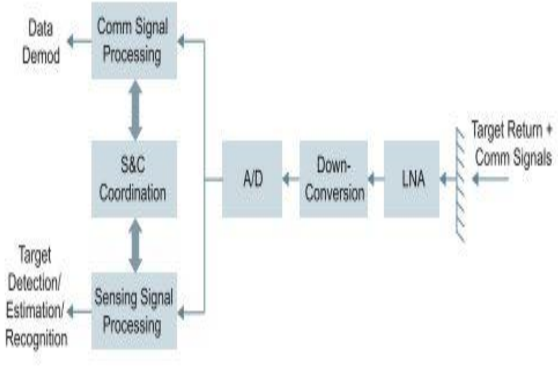

Figure 5: General structure of an ISAC receiver.

## V. COMMUNICATION-ASSISTED SENSING: PERCEPTIVE MOBILE NETWORK

The sensing feature is projected to be included in the next-generation wireless network to build a perceptible network [17], [27], [28], becoming a native capability that offers users different sensing services such as location, recognition, and imaging. In this way, communication may help to sense with the two tiers of design methods listed below:

1) Frame-Level ISAC: Default communication frame architectures and protocols, like Wi-Fi 7 and 5G NR, allow sensing.

2) Network-Level ISAC: Distributed/networked sensing is facilitated by cutting-edge wireless network topologies like Cloud-RAN (C-RAN).

A perceived target might be either a communication or a non-communication item. The first instance frequently arises in high mobility circumstances, when a BS/UE desires to connect to a mobile computing device and simultaneously monitor its movement, as is common in V2X, or UAV connections. In the second situation, the target is frequently part of the surrounding environment and must be identified, recognized, or even photographed for subsequent applications such as high-precision mapping.

Sensing in a PMN can be accomplished by the use of downlink or uplink messages delivered out of a BS or UE, accordingly. As a result, downlink and uplink sensing techniques are defined. To make things clear, the authors divided sensing processes in a PMN among two distinct groups [27]:

1) Downlink Bi-static Sensing: As downlink signals strike the target(s) and then reflect back to another BS, they are used for sensing. This is comparable to bi-static radar in that the receiver and transmitter are well apart.

2) Uplink Bi-static Sensing: The UE transmits uplink signals to the BS, which are used for detection, while the BS receives uplink signals dispersed from the targets. This is yet another example of bi-static radar construction.

### A. Networked Sensing Architecture

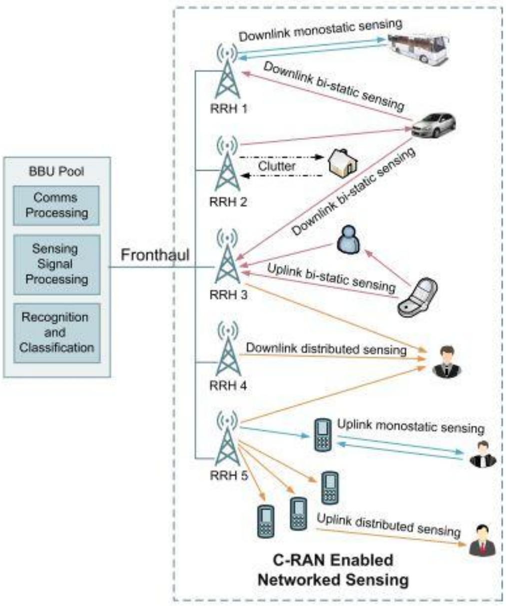

Figure 6: C-RAN Architecture

A typical C-RAN is made up of a collection of baseband units (BBUs), an abundance of remote radio heads (RRHs), and a Front haul infrastructure linking RRHs to BBUs. The BBU pool is located in a centralized location, in which software-defined BBUs process baseband information while coordinating wireless resource distribution. Finally, the BBU pool will be able to function as a main information processing system for networked sensing. The RRHs are in charge of RF amplification, up/down conversion, filtering, analog-to-digital/digital-to-analog conversion, and interface adaptation, and they may be used as radar sensors thanks to the NR waveform and associated ISAC signaling protocols. Finally, the front haul connection is often accomplished through optical fiber communication protocols having significant bandwidth and minimal latency, which may be used to reliably carry both S&C data [29].

## VI. Sensing Assisted Communication: Beam Tracking

After the communication link has been created, for example, the very first connection is accomplished through beam training, the transmitter, as well as the receiver, must continue monitoring the disparity of the optimal beam pairs in order to maintain the level of interaction, and this is referred to as beam tracking [30], [31]. Beam tracking systems make use of the periodic correlation between neighboring signal blocks, utilizing previously estimated beams as prior knowledge for the present epoch. This allows the beams' search zone to be kept within a limited time frame centered on the preceding beam, preventing the transmission of duplicate pilots. Nonetheless, in each beam tracking cycle, the receiver must report the ideal beam index all the way to the transmitter Furthermore, a radar sensor installed on the transmitter can be used to eliminate the feedback loop.

Consider the ISAC-enabled V2I downlink depicted in Fig. 7, where an RSU with $N_t$ transmission and $N_r$ receiving antennas serves a single-antenna automobile in the LoS channel. An ISAC transmission message is sent block by block. The automobile's state is represented in the nth transmitting block by $X_n = [d_n, V_n, \theta_n]^T$, where $d_n$, $V_n$, and $\theta_n$ are the vehicle's distance, velocity, and angle of azimuth relative to the RSU, which are considered to remain constant inside a single block.

Assume that following the arrival of the automobile, the first access is obtained through a radar-aided beam training approach, from which the RSU obtains the parameter estimates $\hat{x}_0 = \left[\hat{d}_0, \hat{v}_0, \hat{\theta}_0\right]^T$. Next the RSU will follow the procedures below to track and anticipate the car's status.

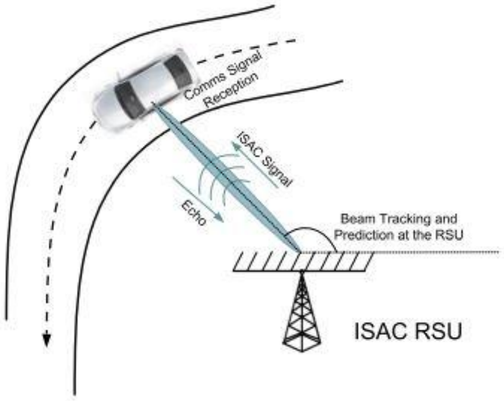

Figure 7: ISAC-enabled V2I downlink system.

1) State Prediction: The RSU forecasts the car's status of the nth epoch at (n − 1)th epoch as

$$\hat{\mathbf{x}}_{n|n-1} \triangleq \left[\hat{d}_{n|n-1}, \hat{v}_{n|n-1}, \hat{\theta}_{n|n-1}\right]^T = \mathcal{P}\left(\hat{\mathbf{x}}_{n-1}\right), (14)$$

In this case, $\hat{x}_{n|n-1}$represents the nth anticipated state based on the (n − 1) Th estimation, while P (•) is a predictor that may be created using either model-based or model-free approaches. While model-based prediction normally depends on the kinetic model of the vehicle, model-free techniques may be developed using artificial intelligence models, which is especially beneficial in complicated traffic situations and channel circumstances.

2) Beam forming: During the nth epoch, the RSU will broadcast a subsequent ISAC signal to the car using the expected angle$\hat{\theta}_{n|n-1}$.

$$\tilde{\mathbf{s}}_n(t) = \mathbf{f}_n^H s_n(t), \qquad (15)$$

$\mathbf{f}_n$ And $s_n(t)$ are, respectively, the probabilistic beamformers with the unit-power information stream planned for the automobile at epoch n.

The beam former $\mathbf{f}_n$ is obtained by

$$\mathbf{f}_n = \mathbf{a}\left(\hat{\theta}_{n|n-1}\right) \qquad (16)$$

Here $\mathbf{a}(\theta) \in \square^{N_t \times 1}$ represents the broadcast steering vector. As a result, the signal that was directed at the car may be written as

$$\mathbf{y}_{C,n}(t) = \boldsymbol{\alpha}_n a^H(\theta_n)\mathbf{f}_n s_n(t) + \mathbf{z}_{C,n}(t) \qquad (17)$$

$\boldsymbol{\alpha}_n$ And Zc (t) denotes the coefficient of the channel and the AWGN, respectively, having a mean of zero and a variance of $\sigma_C^2$. The possible rate may be calculated as follows:

$$\mathbf{R}_n = \log\left(1 + \frac{|\alpha_n a^{H}(\theta_n)\mathbf{f}_n|^2}{\sigma_{C,n}^2}\right) \quad (18)$$

If the angle of prediction is sufficiently precise, i.e., $|\hat{\theta}_{n|n-1} - \theta_n| \approx 0$, the resultant high beam forming gain $a^{H}(\theta_n)\mathbf{f}_n$ is capable of supporting reliable V2I communications.

3) State Tracking: The ISAC transmission is partially accepted by the car's receiver while a portion is returned to the RSU once it strikes the automobile. The recorded echo signal at the RSU may be represented mathematically as

$$\mathbf{y}_{R,n}(t) = \beta_n e^{j2\pi f_{D,n} t} b(\theta_n) a^{H}(\theta_n) x \mathbf{f}_n s_n(t - \tau_n) + \mathbf{z}_{R,n}(t) \quad (19)$$

The nth state can be estimated as

$$\hat{\mathbf{x}}_n = \mathcal{F}(y_{R,n}) \quad (20)$$

On the other hand, by considering the prediction $x_{n|n-1}$, the Kalman filter, can be used to increase estimation precision. This can be stated as

$$\hat{\mathbf{x}}_n = \mathcal{F}_B(y_{R,n}, \hat{\mathbf{x}}_{n|n-1}) \quad (21)$$

The estimate $\hat{\mathbf{x}}_n$ is subsequently used as the predictor's input during the (n + 1) Th iteration. The RSU has the ability to maintain a pace with the movement of the vehicle while maintaining a high-quality V2I downlink by repeatedly conducting state/beam prediction and tracking.

In Figure 8, we analyze a situation in which a 64-antenna RSU supports a car on a straight path, and the automobile moves from one location to the other at an average distance of twenty-five meters with a velocity of 18 meters/s, crossing by the RSU. Because the RSU broadcasts at constant energy, its transmission rate climbs and subsequently declines. Authors contrast the ISAC technique's attainable performance employing extended Kalman filtering (EKF) versus a feedback-based communication-only strategy, specifically the auxiliary beam pair (ABP) tracking approach reported in [31]. Though the ISAC system preserves a somewhat steady rate, the ABP technique's attainable rate drops dramatically to 0 at 1040 ms when it has lost track of the car's angle. This further demonstrates ISAC signaling benefits for V2I beam tracking as well as forecasting.

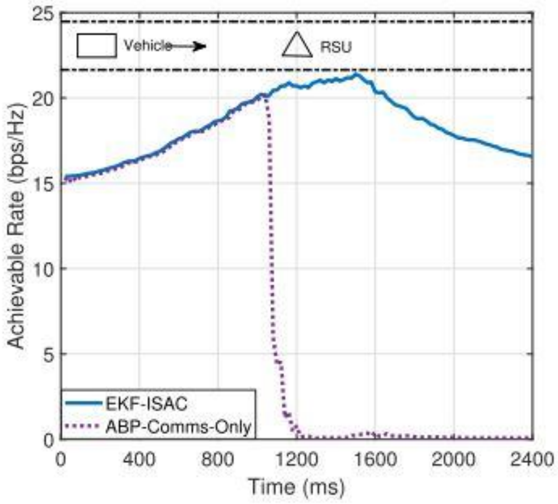

Figure 8: Rates comparison of the ISAC based and communication only beam tracking schemes.

## VII. APPLICATIONS OF INTEGRATED S&C

- Uav monitoring and handling
- Area imaging
- For intelligent homes & In-Cabin Sensing
- Vehicle-to-Everything (V2X)
- Manufacturing Automation and Industrial Internet of Things (IoT)
- Human-computer interactions
- Satellite Navigation and Geosciences
- Environmental Tracking

## CONCLUSION AND FUTURE SCOPE

Sensing and Communication tasks can now be done at several levels rather than just the PHY. An intriguing example is mobile sensing and wireless sensing, wherein commercial wireless gadgets are used for communication between devices in addition to higher-layer sensing operations, such as human movement identification, and this usually happens by developing a deep neural network through sensory information.

The study described the overall structure for PMN, a framework capable of significantly integrated sensing backed by 5G-and-Beyond frequencies and network topologies, notably frame-level ISAC & networking-level ISAC. Downlink bi-static detection among RRHs is a particularly promising technology throughout all sensory operating modes. Because RRHs are linked with the BBU pooling via front haul lines, the SSB signal and data payload delivered by one RRH may be directly recognized by other RRHs by coordination and therefore used for sensing. Because of the high capacity & minimal latency fiber optic front haul, costly phase noise correction and synchronization methods are no longer required.

While many technological hurdles remain in ISAC's core principle, signal analysis, and networking elements, great research initiatives from industry and academia are progressing toward making ISAC operational in the forthcoming wireless communication networks. There is a certainty that ISAC would not just form the basis for entirely novel air interfaces for the 6G network's infrastructure but additionally will also function as the link between the real and virtual environments, where all things are sensed, linked, and smart.

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