MaxRay: A Raytracing-based Integrated Sensing and Communication Framework

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Abstract—Integrated Sensing And Communication (ISAC) forms a symbiosis between the human need for communication and the need for increasing productivity, by extracting environmental information leveraging the communication network. As multiple sensory already create a perception of the environment, an investigation into the advantages of ISAC compare to such modalities is required. Therefore, we introduce MaxRay, an ISAC framework allowing to simulate communication, sensing, and additional sensory jointly. Emphasizing the challenges for creating such sensing networks, we introduce the required propagation properties for sensing and how they are leveraged. To compare the performance of the different sensing techniques, we analyze four commonly used metrics used in different fields and evaluate their advantages and disadvantages for sensing. We depict that a metric based on prominence is suitable to cover most algorithms. Further we highlight the requirement of clutter removal algorithms, using two standard clutter removal techniques to detect a target in a typical industrial scenario. In general a versatile framework, allowing to create automatically labeled datasets to investigate a large variety of tasks is demonstrated.

I. INTRODUCTION

Integrated Sensing And Communication (ISAC) is widely seen as the natural evolution of communications-only networks. In the next generation of wireless network standards, ISAC will enable the already existing communication links to extract environment information [1], [2]. The synergy between communications and sensing could be then leveraged [3]. Although sensing is seen as a new topic in the world of communication, we want to emphasize that both worlds are learning from each other, e.g., Radio Detection And Ranging (RADAR) applications use communication principles like multiple input multiple output (MIMO) and orthogonal frequency division multiplex (OFDM) [4], [5]. On the other hand, proof of concepts where communication networks can locate their users have already been published [6]. However, not only active users can be located, but wireless link can also be used to detect passively the activity of humans [7], their gestures [8], or their position [9].

Although seeing the two worlds merging towards a joint system, a complete redesign of them to fully unveil their potential is still to be done. Among the open points, the channel models typically considered for communications are statistical [10]. The main shortcoming of these models is that they not consider the interaction among the environment and the signals propagating through it in a deterministic way, thus not allowing to perform any meaningful investigation about sensing. Therefore, raytracing can be considered allowing to model the deterministic wireless network signal’s propagation in the environment. Moreover, raytracing offers the capabilities to reproduce the response of additional sensors, like Light Detection And Ranging (LIDAR) and cameras. This allows to investigate not only ISAC, but also sensor fusion techniques.

Therefore, we introduce MaxRay, a versatile tool to simulate realistic scenarios, leveraging ray-tracing to get ISAC channel responses. Moreover, MaxRay allows to deploy and generate the acquisition of multiple environmental sensors, for instance, LIDAR and cameras. This allows to investigate not only ISAC, but also sensor fusion techniques.

Fig. 1: Block diagram of the MaxRay Framework

1 Link available after review
metrics used in computer vision, RADAR and/or communication systems. The sensitivity of these metrics with respect to the AGV tracking precision is discussed, providing suggestions on which are the metrics to be evaluated for network sensing applications.

Summarizing our contributions

• we discuss the viability of raytracing to investigating ISAC,
• we investigate clutter removal performance in an indoor factory scenario and ISAC parametrization, defining and assessing different metrics to measure the performance,
• we provide the labeled dataset to reproduce our results.

The dataset can be used for other ISAC and/or sensor fusion studies.

II. MaxRay: A versatile ISAC Framework

Fig. 1 depicts the workflow of MaxRay, where the input is a dynamic scenario encapsulated as a Blender [11] file and configuration file. This configuration file contains the communication settings, e.g. carrier frequency and number of subcarriers. The power of using Blender is modeling realistic environments, where fine-granular movement of parts and complex scenarios can be simulated. Exploiting the Python Application Programming Interface (API) [11] the exact information about the environment can be leveraged by a ray tracer, getting the communication channel impulse response. Thus, we give a rough overview of the pipeline before explaining the parts in detail.

First, all possible paths considering different propagation properties (reflection, scattering, diffraction, blockage) are calculated using this API and their interactions based on the incident angle, outgoing angle, materials, and speed of the surface are denoted. This computationally complex process is done within the Blender environment and then passed through the following routine within MaxRay: Leveraging those parameters, all experienced losses per path (reflection loss, penetration loss...) are calculated. Then, a Doppler component (phase shift) per path is added, corresponding to the movement of each interacted frame. Further the OFDM frame structure is superimposed by band-limiting the signal and applying the Fourier-transform. On this OFDM frame the corresponding sensing/RADAR images can be calculated.

In general the outputs of MaxRay can be a rendered Camera, a depth and/or a LIDAR image containing all back-scattering points and their distance. Further, the bounding boxes for the camera, the LIDAR object identification per point, the depth bounding boxes and the original position and dimensions of the objects in the environment, are created automatically. We are emphasizing that a full pipeline for different deep learning (DL) or classical techniques is created and the datasets will be available to reproduce our results.

A. Geometrical RayTracing

The pseudo-code of the geometrical ray-casting is given in Alg. 1. The input is a set of probing vectors $\mathbf{P}$ seen from the transmitter point into the environment, compare the blue solid lines of Fig. 2 as an example. Thus, $\mathbf{P}$ defines the spatial resolution and accuracy of the ray-tracing engine, as the initial number and resolution of rays are set by the user. Note in our case we set it to the full angle domain using a resolution of $1$. Then, in a recursive fashion each ray is traced, allowing it to penetrate, diffract, back-scatter and reflect from the objects. Thus, the function "ray()" calculates from the position $\mathbf{p}$ into the direction $\mathbf{t}$ the next interacting object, returning if and at which location (point) an interaction occurred. From this location, the function "calc-new-probes()" calculates using all propagation effects a new set of probing vectors, which will be explained in Alg. 1. This path is stored and broken if at any point a bounding box at the receiver is hit, e.g. by calling the function "check-if-rx-hit". For this to be more efficient, a cube around the receiver of four times the wavelength $\lambda$ is considered. After computing each path, up to the $\ell$-th interaction, their corresponding delays and losses will be calculated.

![Algorithm 1 Geometrical ray-casting](image)

Fig. 2: Different interactions with objects

Fig. 2 depicts for an input vector (blue)

- the back-scattering component by inverting the direction of the input vector,
- the reflected vector by mirroring the input vector,
- the scattering vector created by a pre-defined angular spread of, e.g. 10 degrees and resolution of 1 degree a set of rays around he reflected ray,
- the penetration vector by using Snell’s-law,
multiplying all effects along the path. Hereby

\[ P_{\text{loss}} = \Gamma_{\text{path}} \Gamma_{\text{beam}} \Gamma_{\text{reflect}} \Gamma_{\text{scat}} \Gamma_{\text{rough}} \Gamma_{\text{diffract}} \Gamma_{\text{backscatter}}, \]

(1)

is required, using the Bessel function of zero-th order \( J_0 \) and the standard deviation of the surface roughness \( \rho \). This roughness loss is to model the interaction of high frequency waves at surfaces where the roughness is comparable to the wavelength. The diffraction loss

\[ \Gamma_{\text{diffract}}(\nu) = \frac{\sqrt{(1 - C(\nu) - S(\nu))^2 + (C(\nu) + S(\nu))^2}}{2}, \]

(6)

is commonly modeled using the ITU-R P.526-14 standard \[13\]. Hereby we use the knife-edge diffraction by calculating the geometrical factor \( \nu = \sqrt{\frac{2d}{\alpha_1 \alpha_2}} \), where the angles \( \alpha_1, \alpha_2 \) are between the top of the obstacle and one end as seen from the other end. Moreover, the Fresnel integral

\[ F(\nu) = C(\nu) + jS(\nu) \]

(7)

is approximated by using the cosine integral \( C(\nu) \) and the sine integral \( S(\nu) \). For more details we refer to \[13\]. The last effect considered is the back-scattering loss

\[ \Gamma_{\text{backscatter}} = P_{\text{scat}} \left( 1 + \cos \phi \right) \frac{\alpha_2}{2}, \]

(8)

where we consider the input angle \( \phi \) and the specific back scatter loss \( P_{\text{scat}} \) as the main back-reflection component. One can derive that if the incoming angle is close to zero the effect of back-scattering is stronger than if the ray emerges from the side.

C. Baseband channel representation

Blender and its animation feature can be used to calculate the effective movement between animated frames, allowing to calculate the effective Doppler phase-shift

\[ \beta = 4\pi (N_{\text{sub}} + \text{CP}) f_s f_c \frac{v_s}{c_0} \]

(9)

per path. \( N_{\text{sub}} \) is the number of subcarriers, CP the cyclic prefix length, \( f_s \) the sampling rate, \( f_c \) the carrier frequency, \( c_0 \) the speed of light in the vacuum and \( v_s \) the relative speed in each path-element. This Doppler shift is applied per path at the receiver. As each transmission scheme has a certain bandwidth, the channel impulse response is now decimated. The wanted OFDM frames are created by zero-padding this band-limited channel impulse response and applying the Fourier transform.

The OFDM frames, additional sensory and corresponding labels are saved into a large Hierarchical Data Format (HDF) file. Although one would now expect measurements to verify the ray-tracing core we shift this investigation to a later point, emphasizing that we are not claiming to create a good match between measurements and simulation, but claiming that the underlying structure within behaves the same.

III. Sensing Basics

For understanding the full leverage of ISAC, first the basics of sensing needs to be understood. Thus, we first explain the basic sensing concepts and show the challenges of such systems.
A. OFDM RADAR

Considering that standard communication systems use OFDM, we are going to exploit the concept of OFDM RADAR [4] for sensing. Thus, knowing for each of the $N_{\text{symb}}$ transmitted symbols, the transmitted data $X \in \mathbb{C}^{N_{\text{symb}} \times N_{\text{symb}}}$, the channel

$$H_{k,n}^{(m)} = \mathcal{Y}_{k,n}^{(m)} \mathcal{X}_{k,n}^{(m)}$$

is estimated for each sub-element $k$, $n$, using the single-tap equalizer. Exploiting that only a limited amount of paths $L$ is seen by the received, the channel can be rewritten into

$$H_{k,n} = \sum_{\ell=0}^{L} p_{\text{loss}} e^{j2\pi T_{0}\ell} e^{j2\pi k d_{\ell}/c_{0}} + \Delta f + N_{k,n}^{(m)},$$

where the Doppler frequency shift $f_{\ell}$ of each path is creating a phase shift over the OFDM symbols, with $T_{0}$ being the OFDM symbol duration. The distance traveled creates a linear phase shift over the subcarriers with $\Delta f$ being the sub-carrier spacing. The zero-mean Gaussian distributed noise sample is given by $N_{k,n}^{(m)}$. Thus, one can directly conclude that the phase information per object can be used to determine the relative speed and the range of the object. The angle of the object is estimated by the phase-difference between antennas, i.e. having multiple $H_{k,n}^{(m)}$. The baseline to exploit this orthogonality is represented by calculating the periodogram of the channel $H_{k,n}^{(m)}$.

Therefore, subspace methods were proposed to exploit the underlying channel covariance matrix

$$\mathbf{R} = \mathbf{H} \mathbf{H}^{\dagger}.$$  

One prominent candidate is Multiple Signal Classification (MUSIC) [14], as it exploits the noise subspace of the covariance matrix, which is calculated using the eigenvector decomposition (EVD) of $\mathbf{R}$ and partitioning the eigenvectors into the signal subspace $\mathbf{U}_{S}$ corresponding to the $Q$ strongest eigenvalues and the complementary noise subspace $\mathbf{U}_{N}$. This noise subspace is probed using the the corresponding steering vectors

$$\mathbf{a}(\phi_{q}) = \left[ 1, e^{j2\pi\frac{d_{q}}{\lambda} \sin(\phi_{1})}, \ldots, e^{j2\pi(N_{\text{sub}}-1)\frac{d_{q}}{\lambda} \sin(\phi_{1})} \right]^{T}$$

$$\mathbf{b}(d_{q}) = \left[ 1, e^{-j2\pi \Delta f d_{q}/\lambda}, \ldots, e^{-j2\pi (N_{\text{sub}}-1) \Delta f d_{q}/\lambda} \right]^{T}$$

where $\mathbf{a}$ is the angular and $\mathbf{b}$ the range steering vector, with $f_{D}$ being the Doppler frequency-shift, $N_{\text{sub}}$ being the number of antennas of a uniform linear array with $\lambda/2$ spacing. The 2D MUSIC spectrum (range-azimuth) is obtained by computing

$$P_{\text{MU}}(d, \phi) = \frac{1}{(\mathbf{a}(\phi) \otimes \mathbf{b}(d))^{H} \mathbf{U}_{N} \mathbf{U}_{N}^{H}(\mathbf{a}(\phi) \otimes \mathbf{b}(d))},$$

where $\otimes$ is the Kronecker product. For now we consider the RADAR plot always to be the 2D-MUSIC equivalent.

B. Challenges of sensing

In this paper we assume that the co-located transmitter and receiver are synchronized, giving an upper bound for performance. To show the algorithmic challenges we consider a static scenario first, e.g. Fig. [3] depicts for a specific time instant (frame) the camera and Fig. [5] shows the AGV movement within the experiment. Note, the floor-map corresponds to a typical future production cell [15], consisting of four robots in a specific configuration and an AGV transporting materials within. For this investigation we use a carrier frequency of $f_{c} = 3.75$ GHz, bandwidth of 100 MHz, MIMO configuration of $1 \times 4$ using a linear patch array, 100 symbols and 1024 subcarriers.

C. Clutter Removal

Clutter is defined in general as the interference, noise and reflection from unwanted targets. The task of clutter removal is therefore to remove any signal not being impacted by the AGV.

1) Reference method: This reference clutter removal method is based on measuring the average environment with and without the AGV within $\mathbf{H}$ and $\mathbf{H}_{\text{ref}}$ respectively. Then, we subtract the reference $\mathbf{H}_{\text{ref}}$ from the measurement.

Fig. [5] depicts left the original 2D-MUSIC plot and in the middle the output of clutter removal using the reference method. Thus, the wanted target (AGV) at a range of $\approx 28$ m and 50° is clearly visible. It can be shown that the clutter removal works very good if the scenario is kept.

2) Dynamic method: Another method to remove clutter and to detect a moving object is to estimate the phase shift over time of the individual impulses, by

$$\Delta h = \sum_{p=0}^{N_{\text{symb}}-1} \mathbf{H}^{p,0} e^{-j2\pi p} - \sum_{p=0}^{N_{\text{symb}}-1} \mathbf{H}^{p,N_{\text{symb}}} e^{-j2\pi p}.$$
Using the condition that an impulse not affect by movement should have no phase difference over the frame (besides noise), the impulses in the time domain are set to zero with $\Delta h \leq \epsilon$, where $\epsilon$ is arbitrarily set to 1%. Fig. 5 shows the impact of this clutter removal technique (right), removing partly the clutter. Thus, this technique enhances the RADAR image, by de-cluttering. The importance of finding a suitable metric to compare those two clutter-removal techniques is emphasized by understanding that the visual effect does not give any possibility of numerically assess their performance, for fine-granular comparisons.

### D. Metrics

Although in vision-based systems different metrics were introduced, RADAR images have the unique twist of not knowing if and how

- the target is "seen" by the receiver (there is a reflection),
- the size of the objects impacts the receiver image,
- the exact position and reflection are accounted for.

To demonstrate the advantages and disadvantages of this techniques we leverage first a static frame, where the ground-truth is known. In general, we assume that peaks can be detected if their amplitude/power is at least 10% higher power than the average power of the RADAR image. We consider now four different metrics, where the probability of detection emerged from vision technologies, the signal-to-interference-and-noise-ratio (SINR) metric from communication, the prominence and isolation from geology.

1) **Probability of Detection**: The probability of detection is defined as

$$P_D = \frac{N_{\text{detected}}}{N_{\text{iteration}}} \cdot 100\%$$ (19)

where $N_{\text{detected}}$ is the number how often the AGV was detected within a range of $\lambda$ around the true target and $N_{\text{iteration}}$ is the number of the experiment runs. Plotting this metric over the movement of the AGV demonstrates potential blockers and thus can be leveraged to enhance communication. This metric is also heavily impacted by defining the range difference allowed, making erroneous peaks possible in low signal-to-noise-ratio (SNR) regions.

2) **SINR**: Another metric is the SINR

$$\Gamma = \frac{P_{\text{Signal}}}{\sum P_S},$$ (20)

where the power at the specific position in the RADAR image $P_{\text{Signal}}$ is taken and then divided by the remaining power $P_S$ in the set $S$ outside the $\lambda$ circle. Note, this metric incorporates targets which are not wanted as interference and thus punishes clutter-removal techniques which keep background targets (dynamic method).

3) **Prominence**: Prominence

$$\kappa = \frac{P_{\text{Signal}}}{P_c}$$ (21)

is a metric mostly used in topography maps and is defined as the distance between the wanted signal (peak) $P_{\text{Signal}}$ and the circumference $P_c$ around this peak, where the gradient changes its sign.

4) **Isolation**: Isolation

$$\iota = |p_{\text{peak}} - p_{\text{closest,peak}}|^2$$ (22)

is given as the distance between the signal peak $p_{\text{peak}}$ to the next peak $p_{\text{closest,peak}}$. Note that this metric is unbounded if only one target is available. Fig. 5 depicts in this simple case the performance for the different clutter removal techniques using the mentioned metrics. It can be seen that since the noise can create erroneous peaks at the wanted position, the probability of detection is falsely large at low SNR, but converges to the real probability in high SNR regions. As seen from the visualization in the clutter removal section the reference case is better than the dynamic removal but still achieves a lot better results than without. Thus, both techniques seem to be viable at first. The SINR metric punishes that the second peak of the clutter is not removed, thus no real gain is shown and it seems to be an unsuitable metric (comp. Fig. 5). The prominence in the sub-figure does not show the effect of the low SNR error as the prominence in noise is almost zero. Further it shows...
the respective gains of the clutter removal, rendering it into a very viable metric for sensing algorithms. The isolation in the last sub-figure shows the gains, but is unbounded due to only a remaining peak, when the SINR is high enough. In conclusion it seems that prominence due to its bounding by zero and one, incorporates all underlying effects and is suitable for the most classical and DL techniques. After knowing the behaviour of the probability of detection and prominence in the static case, we move further to another experiment where we run the AGV on the track shown in the Fig. 3b and investigate the time behaviour (blockage) and the changes if one of the robots moves (environmental movement).

E. Dynamic environment

Fig. 6 shows the probability of detecting the AGV using the two clutter removal techniques. It can be seen that the reference case only has two dips at exactly the positions of the robotic arm (e.g. blockage). Further due to the limited angular resolution the AGV cannot be resolved. In the case of the dynamic clutter removal the channel impulse response in some cases cannot resolve the target, thus making it unsuitable for perfect tracking. Note that time tracking can enhance this method. In this case communication can benefit from sensing systems by predicting blockage, and therefore performance drops, beforehand.

F. Environmental movement

Fig. 7 depicts the performance, if one of the robots arm moves, while the AGV moves, degrading the performance of the reference method. This is due to the effect that the reference method only incorporates a specific setting and the reflections within the environment drastically change if the environment changes. Notably the performance of the dynamic clutter removal stays constant and even improves a little, due to better separation of static parts. Further the dynamic case seems to be achieving the most promising results, which could be used to calculate the RADAR image.

IV. Conclusion

A versatile framework capable of simulating ISAC systems using realistic scenarios due to the virtue of Blender was introduced. The required workflow of such a sensing framework to incorporate all necessary propagation attributes was demonstrated. Further four commonly used metrics from different fields were compared regarding their ability to capture the sensing capabilities. As it turns out prominence due to its noise resilience and being bounded is a strong candidate for creating a common comparison technique among a large amount of different algorithms. In a standard industrial use-case state-of-the art clutter removal techniques were compared, demonstrating that clutter removal is a key element for the success of ISAC systems. Additional scenarios and datasets will be provided in the future to reproduce and compare algorithms.

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