Object Distance Estimation from Electromagnetic Interactions in Robotics

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Abstract. Estimating an object's distance from electromagnetic wave interactions is critical for robotic perception - especially in scenarios with occlusion or degraded visibility. Traditional radar systems rely on handcrafted signal processing pipelines which limit adaptability to novel sensor configurations. In this work, we present a hybrid approach that combines lightweight signal processing with a data-driven inverse mapping from transmit–receive wave measurements to object distance. We first transform raw signals, FMCW radar intermediate-frequency signals and S-parameters, into the frequency and time domain, respectively, applying peak detection and Hamming windowing to extract propagation path features. These features are then used to train Gaussian Process Regression models that predict object coordinates with uncertainty estimates. We evaluate the method on both simulated S-parameters and measured radar data designed to emulate future flexible electromagnetic skins. The results demonstrate enhanced sensing modalities and inherently learned geometry of the sensor, highlighting the potential of combining minimal signal preprocessing with probabilistic learning for general-purpose robotic electromagnetic perception.

Keywords: Gaussian Processes, Radar, S-parameters, Distance Estimation

1 Introduction

Electromagnetic (EM) wave-based sensing, in which a system actively transmits and receives signals that interact with the environment, plays a central role in modern robotic perception (e.g. lidar and radars). EM sensing enables robust operation in adverse conditions such as darkness, dust, fog, or partial occlusion, making it attractive for safety-critical robotic applications. Recently, flexible EM sensing paradigms have been explored, including active robotic skins that enable dense near-field perception over large surface areas. Such systems are commonly characterized using scattering parameters (S-parameters), which provide a compact representation of how electromagnetic waves propagate and interact within multi-port networks, and are widely used in microwave engineering [1, 2].

This research direction is actively explored within the EU Pathfinder Open project *Flexible intelligent near-field sensing skins (FITNESS)*[1], which aims to develop intelligent sensing skins capable of perceiving objects through surface and leaky-wave propagation. These approaches have the potential to significantly enhance sensing capabilities compared to existing stretchable electronic skins, which are typically based on pressure, piezoelectric, piezoresistive, or capacitive sensing [3].

At the same time, radar-based robotic perception has undergone a rapid methodological evolution. Traditional Frequency-Modulated Continuous Wave (FMCW) radar pipelines rely on deterministic signal processing to estimate range, angle, and Doppler, producing structured representations such as 3D or 4D radar point clouds. Building on these representations, the majority of radar-based object detection, tracking, and ego-motion estimation methods rely on scan registration. Consequently, recent works have focused on improving scan registration [4], performing online extrinsic or temporal calibration between radar and IMU [5, 6], or integrating radar and LiDAR data [7], among others. More recently, end-to-end learning-based approaches have begun to operate directly on low-level radar signals, including ADC samples, for tasks such as object detection and velocity estimation [8, 9].

In this paper, we address two limitations of existing learning-based radar distance estimation approaches. First, many prior methods rely on heavily preprocessed signal representations that are tightly coupled to specific sensor configurations, thereby limiting generalization. Second, despite its importance for downstream robotic tasks such as tracking, uncertainty estimation is often neglected. To overcome these limitations, we propose a unified probabilistic framework for distance estimation from EM stands wave interactions. Our approach builds upon an established signal processing pipeline and refines its outputs through Gaussian Process regression (GPR) [10], enabling both accurate predictions and well-calibrated uncertainty estimates.

Importantly, the proposed method requires supervision only in the form of ground-truth distance measurements for training. This significantly reduces data requirements compared to conventional deep learning–based approaches, which typically operate on raw sensor data and often needs to implicitly learn complex transformations such as Fourier transforms.

We focus on distance estimation rather than object detection to examine the relationship between EM wave scattering and geometric distance. The proposed model applies to both standard FMCW radar and emerging near-field sensing modalities based on flexible metasurfaces pipelines, and can inherently learn sensor geometry without explicit calibration. To demonstrate the generality of the approach across different sensing configurations, we validate the method on both a two FMCW radar setup and a six-port antenna configuration. For evaluation, we use simulated S-parameter data from a six-port 10 GHz antenna array and measured data from two 24 GHz FMCW radars. S-parameters are

[1] https://fitness-pathfinder.eu

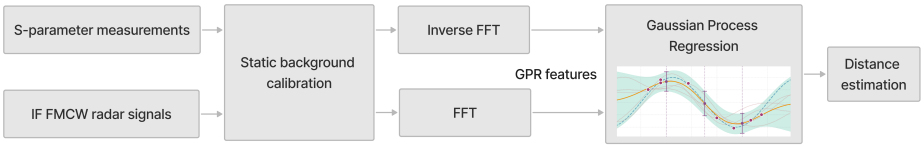


Fig. 1: Overview of the proposed pipeline for distance estimation using FMCW radar signals or S-parameter measurements.

processed in the time domain and FMCW radar signals in the frequency domain, with peak-based features used as inputs to the GPR model.

The proposed approach improves distance estimation accuracy across sensing modalities compared to preprocessing-only methods, while providing uncertainty estimates. It requires no explicit geometric assumptions, enabling geometry-aware EM perception for future robotic systems through minimal signal preprocessing and probabilistic learning.

2 The proposed method

Numerous methods exist for distance estimation using FMCW radar and frequency-domain S-parameter measurements. Conventional FMCW pipelines rely on signal preprocessing, peak detection, and Constant False Alarm Rate (CFAR) filtering. In contrast, we focus on distance estimation rather than detection, exploiting FMCW intermediate-frequency (IF) signals and S-parameters in a data-driven manner. We assume access to ground-truth distances during training and propose a lightweight GPR-based approach that does not require large-scale data collection.

Figure 1 illustrates the overall pipeline. S-parameter and FMCW IF measurements are first differenced with respect to a known reference response obtained in an empty environment (i.e., without an object), and transformed into the time and frequency domains for S-parameters and IF signals, respectively. Propagation-related features are then extracted and used as inputs to a GPR model for distance estimation. The following subsections describe the preprocessing steps for S-parameter and FMCW radar measurements, and GPR.

2.1 Preprocessing of S-Parameter Measurements

For S-parameter-based sensing, we design a simulation pipeline for Ansys HFSS similar to work in [11]. Rather than interpreting S-parameters analytically, we treat them as frequency-domain observables and transform them into the time domain to expose dominant propagation paths induced by the object.

The parameter S_{ij} represents the ratio of the outgoing power wave at port i to the incident power wave at port j, assuming all other ports are matched. When $i = j$, S_{ii} corresponds to the reflected power at the same port and is referred to as a reflection coefficient. When $i \neq j$, S_{ij} describes transmission between ports [2]. In general, S-parameters are complex-valued, capturing both magnitude and phase variations introduced by the EM environment. S-parameters

are influenced by nearby objects through scattering and impedance changes. We simulate frequency-domain S-parameter measurements for two scenarios: an empty environment and an environment containing a single object with various distances. By subtracting the reference response, we isolate the object-induced perturbation.

The differential S-parameter response is transformed into the time domain using the inverse Fourier transform. To improve temporal resolution and suppress sidelobes, a Hamming window is applied prior to transformation. Peak detection combined with quadratic interpolation is then used to estimate dominant propagation paths, from which effective path length differences are extracted. These path differences serve as indirect measurements of object distance via EM wave propagation. Due to the complex and non-linear relationship between S-parameter variations and object distance, we use GPR [10] to model this mapping. Using a squared exponential kernel, we train independent GPR models to regress the 3D object coordinates (x, y, z) from extracted propagation features. In particular, we evaluate two feature configurations: *(i)* estimated path-length distances only, and *(ii)* distances augmented with the corresponding peak magnitudes. Hyperparameters are optimized by maximizing the marginal likelihood, enabling accurate distance estimation even with limited training data.

2.2 Preprocessing of FMCW Radar Signals

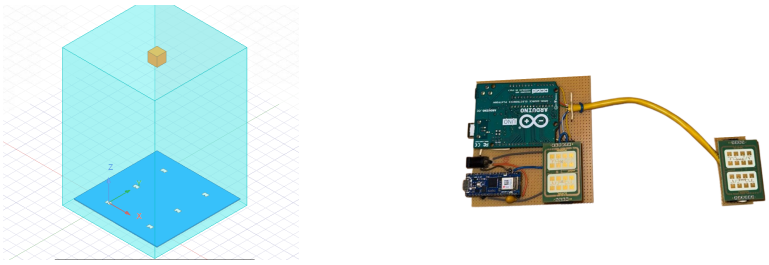
FMCW radars estimate object range by transmitting frequency-modulated chirps and analyzing the resulting IF signal [12]. Conventional pipelines apply an Fourier Transform to the IF signal and identify spectral peaks corresponding to reflecting objects, with CFAR-based processing commonly used for detection and clutter suppression. Since this work focuses on distance estimation rather than detection or velocity estimation, we directly extract stable range-related features from the dominant spectral peaks of the IF signal, including estimated ranges and their corresponding magnitudes.

We evaluate two feature configurations: *(i)* a minimal representation consisting of the estimated ranges from both radars, and *(ii)* an extended representation that augments these ranges with the corresponding peak magnitudes, resulting in a four-dimensional feature vector. These features from multiple FMCW radars are jointly modeled using GPR, enabling the model to inherently capture the underlying antenna geometry.

2.3 GPR for Distance Estimation

The relationship between propagation-related features extracted from EM measurements and object distance is nonlinear and depends on the sensor configuration. To model this mapping while explicitly capturing prediction uncertainty, we use GPR. Let $\mathbf{x} \in \mathbb{R}^D$ denote a feature vector extracted from either S-parameter or FMCW radar measurements, and let $y \in \mathbb{R}$ denote the corresponding object distance or spatial coordinate. We assume the measurement model

$$y = f(\mathbf{x}) + \epsilon, \tag{1}$$



(a) S-parameter simulation (b) FMCW radar setup

Fig. 2: Experimental setups used for model evaluation: (a) EM simulation of S-parameters for a six-element patch antenna array, (b) 2 FMCW-radar experimental setup used for IF signal measurement.

where $f(\cdot)$ is an unknown latent function modeled as a Gaussian process and ϵ represents additive Gaussian noise. A squared exponential kernel is used to model correlations in the feature space, with kernel hyperparameters and noise variance optimized by maximizing the marginal likelihood. For a given test input, GPR yields a Gaussian predictive distribution, providing both a distance estimate and the associated uncertainty.

For S-parameter-based sensing, three independent GPR models are trained to estimate the spatial coordinates (x, y, z), while for FMCW radar measurements a single GPR model predicts the object distance. This formulation enables the model to implicitly capture sensor geometry and propagation effects without explicit calibration.

2.4 Results

In this section, we present results obtained using simulated S-parameter and FMCW IF signal measurements. The evaluation focuses on the accuracy of the proposed GPR framework in estimating object position from time-domain and frequency-domain features. Figure 2 illustrates the experimental setups used for model evaluation, the EM simulation using 10 Ghz antennas used to generate S-parameter data, and the 2 IV-S 362 radar setup setup employed for IF-signal measurements.

2.5 S-parameter Results

The S-parameter evaluation is performed using EM simulations generated in Ansys HFSS. A small rigid object of size $2\,\text{cm} \times 2\,\text{cm} \times 2\,\text{cm}$, modeled as a perfect electric conductor (PEC), is placed at varying positions in front of a six-port antenna configuration, within a workspace defined by $x \in [-4.5, 12.1]\,\text{cm}$, $y \in [-6.0, 18.0]\,\text{cm}$, and $z \in [1.0, 15.0]\,\text{cm}$. For each object position, frequency-domain S-parameters are simulated, and a reference response corresponding to an empty environment is subtracted to isolate object-induced perturbations.

The differential S-parameter responses are processed to obtain a time-domain representation, from which dominant propagation paths are identified using peak

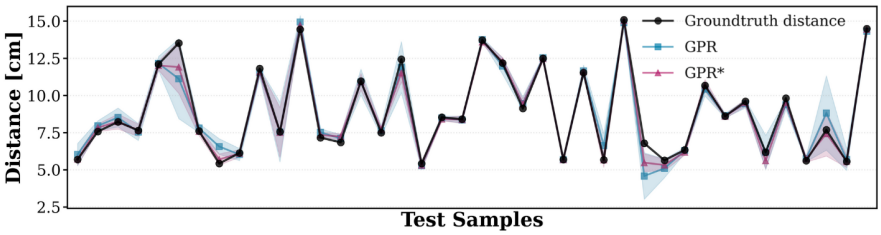


Fig. 3: Comparison of GPR models trained using distance-only features (GPR) and combined distance-and-magnitude features (GPR*) extracted from time-domain S-parameter responses.

detection with quadratic interpolation. From each port pair, the propagation delay and corresponding peak magnitude are extracted and used to form the input feature vector for learning. The input to the learning model consists of time-domain propagation features derived from the S-parameters, while the output corresponds to a single spatial coordinate of the object position. To recover the full 3D position, three independent GPR models are trained, one for each coordinate axis (x, y, z). The dataset consists of 394 simulated samples and is split into 90% training and 10% testing data.

Figure 3 compares two GPR configurations: (i) a model trained using only propagation delay (distance) features, and (ii) an enhanced model trained using both propagation delays and peak magnitudes. When only distance features are used, the mean estimation errors are 0.320 cm, 0.487 cm, and 0.348 cm for the x, y, and z coordinates, respectively, with corresponding standard deviations of 0.500 cm, 0.742 cm, and 0.558 cm. This results in a mean 3D position error of 0.780 cm with a standard deviation of 0.982 cm. In contrast, incorporating peak magnitude information leads to a substantial improvement in localization accuracy. The mean errors are reduced to 0.134 cm, 0.274 cm, and 0.098 cm for the x, y, and z coordinates, respectively, with standard deviations of 0.206 cm, 0.459 cm, and 0.134 cm. The corresponding mean 3D position error decreases to 0.389 cm with a standard deviation of 0.471 cm.

These results indicate that propagation path, together with peak magnitudes information, provide complementary EM and geometric cues, enabling the model to implicitly infer antenna geometry without explicit calibration. Preliminary results on a physical system, trained on simulated data, show promising performance and provide initial validation of the proposed approach.

2.6 FMCW Radars

In this experiment, we evaluate the proposed learning-based distance estimation approach using FMCW radars measurements. Two independent FMCW radars are used, each transmitting identical chirp signals but operating as separate sensing units. In a conventional radar setup, object range can be estimated independently by each radar receiver, or combined analytically using known sensor geometry. However, such estimates are fundamentally limited by the radar bandwidth and range resolution. A small metallic object ($9 \times 7 \times 1$ cm) is translated

Table 1: Distance estimation comparison for FMCW radar measurements.

Method	MAE [cm]	Std [cm]	RMSE [cm]
Radar I.	14.76	8.51	17.04
Radar II.	16.91	8.94	19.13
GPR (2 features)	**8.15**	**6.27**	**10.28**
GPR (4 features)	9.28	7.51	11.94

within the measurement region, with axis-aligned spans of 0.54 m, 0.74 m, and 1.29 m along the OptiTrack x, y, and z axes, respectively. Ground-truth object distance between small metal object and radars are obtained using an OptiTrack motion capture system. In practice, the dominant spectral peak in FMCW radar measurements often corresponds to clutter or multipath reflections, particularly when the object is not in the direct field of view. To mitigate this effect, we apply a simple preprocessing rule and discard detected peaks corresponding to distances below 0.3 m. Such spurious detections would typically be rejected by a dedicated target tracking or detection module, which is currently outside the scope of this work.

Using the described preprocessing pipeline, we evaluate four methods: raw range estimates from each radar independently, and two GPR models using either two or four input features. The dataset consist of 416 valid measured samples, and is split into 80% training and 20% testing data. The two-feature model uses only the estimated ranges from both radars, while the four-feature model additionally integrates the corresponding peak magnitudes.

The results 1 demonstrate that the proposed GPR-based approach improves distance estimation accuracy compared to raw radar range measurements. Using two ranges as input features yields the best overall performance, reducing the mean absolute error from 14.76 cm and 16.91 cm for the individual radars to 8.15 cm, as shown in Table 1. Interestingly, augmenting the input feature vector with peak magnitude information slightly degrades estimation accuracy rather than improving it. This behavior can be attributed to the fact that FMCW radar peak magnitudes are highly sensitive to reflectivity, orientation, antenna patterns, and multipath effects, introducing variability that is weakly correlated with object distance and increases regression uncertainty.

3 Conclusion

In this paper we presented a probabilistic framework for estimating object distance from EM interactions using minimal signal preprocessing combined with GPR. Unlike conventional radar pipelines that rely on explicit geometric models and heavily engineered signal processing, the proposed approach learns an inverse mapping from propagation-related features to object distance.

We demonstrated the applicability of the method across two fundamentally different sensing modalities, frequency-domain S-parameter measurements from a multi-port antenna configuration and intermediate-frequency signals from FMCW radar sensors. In both cases, the proposed framework estimate the distance with high accuracy, despite relying on low-dimensional feature represen-

tations and limited training data. The learning-based model is able to implicitly capture the underlying sensor geometry without requiring explicit calibration or prior knowledge of antenna placement. The proposed framework intentionally focuses on single-object distance estimation in order to isolate the fundamental relationship between electromagnetic wave propagation and geometric distance.

Future work will extend this approach to multi-object scenarios through clutter-aware preprocessing and integration into tracking or factor-graph-based state estimation pipelines.

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