Beam-Space MIMO Radar for Sensing-aided mmWave Communications

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Synergy between Sensing and Communication

- Sensing can provide “side information” for improving communication functions (beam alignment, refinement, tracking, fast handover, fast user-AP association ...)

- Communication can enhance sensing quality (e.g., multistatic radar, sensor fusion, closed-loop protocols).

- Does it make sense to share the same resource (power, bandwidth, hardware)?
Application Scenarios in mmWave Comm.

- **Scenario 1, Discovery**: wide sector transmission (e.g., low-rate control broadcast channel), unknown targets.

- Goal: target detection, parameter estimation to speed-up BA.
**Scenario 2, Tracking:** beamformed transmission (e.g., individual DL data streams), known targets.

- Goal: parameter estimation for beam refinement/tracking.
RF Beamforming and AoA Estimation

- The number of RF chains (demodulation to BB and ADC) is much smaller than the number of antenna array elements.

- For AoA estimation (both Scenario 1 and 2) we need a vector observation.
Because of complexity and power consumption of the A/Ds, a typical mmWave architecture consists of hybrid digital-analog BF.

A number $N_{\text{rf}}$ of RF chains, much smaller than the number of antenna array elements $N_a$, produces a reduced-dimensional “beamspace” baseband channel.
Example of grid of beams for $N_a = 64$.

- Beam-space MIMO radar

$$C = \{\hat{u}_{i,j}\} \quad i = 0, 1, 2, \ldots, \frac{2\theta_{\text{max}}}{\Delta \theta} - 1, \quad j = 0, 1, 2, \ldots, \frac{\Delta \theta}{\delta \theta} - 1$$
Multitarget channel model (1)

- Array response vector (simple case: ULA) \( \mathbf{a}(\phi) = (a_1(\phi), \ldots, a_{N_a}(\phi))^\top \in \mathbb{C}^{N_a} \)
  
  with
  \[
  a_n(\phi) = e^{j(n-1)\pi \sin(\phi)}, \quad n = 1, \ldots, N_a.
  \]

- Backscatter channel model
  
  \[
  \mathbf{H}(t, \tau) = \sum_{p=0}^{P-1} h_p \mathbf{a}(\phi_p) \mathbf{a}^\dagger(\phi_p) \delta(\tau - \tau_p) e^{j2\pi \nu_p t}
  \]

- Multicarrier signal with \( N_s \) data streams
  
  \[
  \mathbf{s}(t) = \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} \mathbf{x}_{n,m} g_{tx}(t - nT) e^{j2\pi m \Delta f(t - nT)}.
  \]
Multitarget channel model (2)

- Received signal at the radar receiver in block $b$

$$r_b(t) = \sum_{p=0}^{P-1} h_p U_b^H a(\phi_p) a^H(\phi_p) F s(t - \tau_p) e^{j2\pi \nu_p t}.$$ 

- $U_b$ is a $N_a \times N_{rf}$ reduction matrix, whose columns are beamforming vectors.
- After chip matched filtering and sampling, blocks $b = 1, \ldots, B$ of $N$ time symbols and $M$ subcarriers can be compactly written as

$$y_b = \left( \sum_{p=0}^{P-1} h_p G_b(\nu_p, \tau_p, \phi_p) \right) x_b + w_b,$$

where we define the effective channel matrix of dimension $N_{rf}NM \times N_sNM$ as

$$G_b(\nu, \tau, \phi) \triangleq \left( U_b^H a(\phi) a^H(\phi) F \right) \otimes \Psi(\nu, \tau).$$
Target detection in Discovery mode (1)

- We do target detection in sequence: at each step we have a binary hypothesis testing problem with hypotheses $H_0$ and $H_1$ correspond to absence or presence of the $p$-th target only.

$$y_b = \begin{cases} w_b & b = 1, \ldots, B \text{ under } H_0 \\ h_p G_b (v_p, \tau_p, \phi_p) x_b + w_b & b = 1, \ldots, B \text{ under } H_1. \end{cases}$$

- The log-likelihood ratio for the binary hypothesis testing problem is given by

$$\ell(h_p, v_p, \tau_p, \phi_p) = 2\text{Re} \left\{ \left( \sum_{b=1}^{B} y_b^H G_b x_b \right) h_p \right\} - |h_p|^2 \sum_{b=1}^{B} \| G_b x_b \|^2.$$
Target detection in Discovery mode (2)

- Since the true value of the parameters is unknown, we use the Generalized Likelihood Ratio Test

\[
\max_{h_p, \nu_p, \tau_p, \phi_p} \ell(h_p, \nu_p, \tau_p, \phi_p) \frac{\mathcal{H}_1}{\mathcal{H}_0} \geq T_r.
\]

- The maximization with respect to \( h_p \) for fixed \( \tau_p, \nu_p, \phi_p \) is immediately obtained as

\[
\hat{h}_p = \frac{\left( \sum_{b=1}^{B} y_b^H G_b x_b \right)^*}{\sum_{b=1}^{B} \|G_b x_b\|^2}.
\]

- Replacing this into the log-likelihood expression we obtain

\[
\ell(\hat{h}_p, \nu_p, \tau_p, \phi_p) = \frac{\left| \sum_{b=1}^{B} y_b^H G_b x_b \right|^2}{\sum_{b=1}^{B} \|G_b x_b\|^2} \overset{\Delta}{=} S(\nu_p, \tau_p, \phi_p)
\]
Target detection in Discovery mode (3)

Sequential detection with SIC:

1. Initialize $p = 1$

2. Compare $S(\nu, \tau, \phi)$ with the adaptive threshold $T_r(\nu, \tau, \phi)$, and find the set $\mathcal{T}$ of points in the Doppler-delay-AoA above threshold.

3. If $\mathcal{T} = \emptyset$, exit (no more targets to be found).

4. If $\mathcal{T} \neq \emptyset$, let the $p$-th target with parameters

   $$ (\hat{\nu}_p, \hat{\tau}_p, \hat{\phi}_p) = \arg\max \{ S(\nu, \tau, \phi) : (\nu, \tau, \phi) \in \mathcal{Y} \} $$

5. Subtract the corresponding signal from the received signal (SIC).

6. $p \leftarrow p + 1$, and go to point 2.
Adaptive threshold for target detection (1)

- The decision threshold is set adaptively from the ordered statistics of samples of $S(\nu, \tau, \phi)$ in a window around the decision point.
Adaptive threshold for target detection (2)

(a) Signal
(b) Threshold
(c) Threshold-passed Signal points


[14] F. Pedraza, M. Kobayashi, and G. Caire, “Beam refinement and user state acquisition via integrated sensing and...
Parameter estimation in Tracking mode (1)

- The log-likelihood function, neglecting irrelevant terms, is given by

\[ \Lambda(\{h_p, \nu_p, \tau_p, \phi_p\}) = 2\text{Re}\{h^Hr\} - h^HAh. \]

where we define the \( P \times 1 \) vector of path coefficients \( h = (h_0, \ldots, h_{P-1})^T \), the vector of signal correlations \( r \) with \( p \)-th element

\[ r_p = \sum_{b=1}^B x_{b,p}^H G_{b,p}^H y_b, \]

and the \( P \times P \) matrix \( A \) with \( (p, q) \) element

\[ A_{p,q} = \sum_{b=1}^B x_{b,p}^H G_{b,p}^H G_{b,q} x_{b,q}. \]
Parameter estimation in Tracking mode (2)

- The maximization with respect to $h$ is readily obtained as
  \[ \hat{h} = A^{-1}r \]

- Replacing this, we find $\Lambda_1(\{\nu_p, \tau_p, \phi_p\}) = r^HA^{-1}r$.

- The problem is further simplified by noticing that $A$ is approximately diagonal. Under this simplification, we obtain
  \[ \Lambda_1(\{\nu_p, \tau_p, \phi_p\}) = \sum_{p=0}^{P-1} \frac{\left| \sum_{b=1}^{B} y_b^H G_{b,p} x_{b,p} \right|^2}{\sum_{b=1}^{B} \| G_{b,p} x_{b,p} \|_2^2}. \]

- Each term in the sum has a form similar to the function $S(\nu, \tau, \phi)$ defined before and can be maximized individually with respect to the corresponding parameters $\{\nu_p, \tau_p, \phi_p\}$. 
Target discovery (scenario)

- **Fig. 3**: Probability of detection of targets vs. SNR within an illuminated angular FoV of 90° with varying B. The bottom plot depicts a two-target scenario where $P_d$ for the second target after detection and removal of the first target is reported.

- **Tracking Mode**: Next, the parameter estimation performance of the Tracking mode is considered where with the assumption of acquired targets, i.e., users, a narrow Tx beam transmits information symbols toward each user via a dedicated RF chain. This results in an increased $G_{\text{Tx}}$ and consequently, SNR, leading to improved estimation performance, while significantly reducing the interference effects of other users. As depicted in Fig. 4, in the simulated scenario three distinct users are considered where the first and second are positioned with a fixed distance and...
Target discovery (results)

![Graph showing probability of detection vs range for single and multi targets]

- **Single Target**
  - Probability of detection, $P_d > 0.9$
  - Graphs for different ranges and BS configurations

- **Multi Target (with SIC)**
  - Graphs for single and multi targets
  - Probability of detection for different ranges and BS configurations

2) Tracking Mode:

Next, the parameter estimation performance of the Tracking mode is considered where with the assumption of acquired targets, namely users, a narrow Tx beam transmits information symbols toward each user via a dedicated RF chain. This results in an increased $G_{Tx}$ and consequently, SNR, leading to improved estimation performance, while significantly reducing the interference effects of other users. As depicted in Fig. 4, in the simulated scenario three distinct users are considered where the first and second are positioned with a fixed distance and...
Target parameter estimation (scenario)

Fig. 4: Simulation Scenario in Tracking mode where each acquired user (target) receives a very narrow signal via a dedicated RF chain.

affects the sharpness of the main peak. This is caused by the fact that left and right shifts of the beam that encompasses the target can lead to a sharpening effect on the beam over multiple integration blocks. Fig. 6 depicts these effects.

VI. CONCLUSIONS

In this paper, we proposed an efficient ML-based algorithm able to jointly perform target detection and radar parameters estimation, i.e., range, velocity, and AoA, by using a MIMO monostatic radar adopting an OTFS modulation and operating in different modes. Simulation results demonstrate the robustness of the algorithm in term of both target identifiability and estimation.
Target parameter estimation (results)

- **RMSE**[$\hat{\phi}$][rad]
  - Tgt 1
  - Tgt 2
  - Tgt 3

- **RMSE**[$\hat{r}$][m]
  - Tgt 1
  - Tgt 2
  - Tgt 3

- **RMSE**[$\hat{\nu}$][m/s]
  - Tgt 1
  - Tgt 2
  - Tgt 3

- **CRLB**($\phi$)
- **CRLB**($\tau$)
- **CRLB**($\nu$)

**Fig. 4**: Simulation Scenario in Tracking mode where each acquired user (target) receives a very narrow signal via a dedicated RF chain.

VI. CONCLUSIONS

In this paper, we proposed a Beam-Space MIMO Radar approach for joint data transmission and radar parameter estimation based on OTFS modulation and targeting mmWave applications. The beam-space approach consists of reducing the Na-dimensional received signal at the radar.

- Related work of ours [14].

[CAN WE REARRANGE THE FIGURES .. PUT THE TOPOLOGY CARTOON IN A DIFFERENT FIGURE .. REFERENCED WHEN DESCRIBING THE NUMERICAL EXPERIMENT, AND TO PERHAPS THE 4 FIGURES ABOVE ARRANGED IN A MORE SPACE EFFICIENT WAY? WITH LABELS?]
Simulation scenario: cars moving on complicated urban trajectories.
• Rate versus time step for a given trajectory

Application to beam tracking in mmWave

- Average rate versus space (rate map), averaged over many trajectories
Conclusions

- Theoretical results (information theory) show that joint communication and sensing sharing the same transmission resource can be very efficient with respect to resource partitioning.

- Advantage of exploiting the same hardware and not polluting further the RF spectrum.

- For high frequency bands (mmWaves and sub-THz) we propose beam-space MIMO radar as an efficient radar receiver with low A/D front-end complexity.

- Results show that new target detection and parameter estimation for already connected users can be done with performance comparable to state of the art automotive radar.

- Application to beam tracking .. and speed-up of initial beam acquisition (ongoing work).
Thank You