

Transformer-Based Multi-Modal Deep Learning for Sensing-Aid Beam Prediction

ITU AI/ML in 5G Grand Challenge 2022

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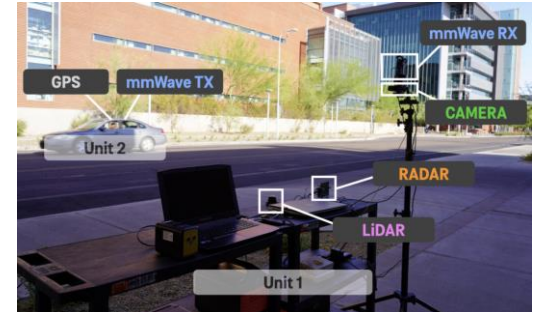
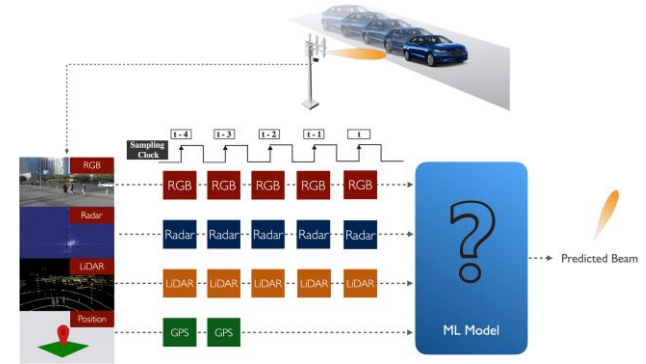
Thanks to Kebin Wu

Outline

- Problem Statement
- Multi-Modal Sensing Data Preprocessing
- Deep Learning for Beam Prediction
- Experimental Results and Discussions
- Conclusions and Future Works

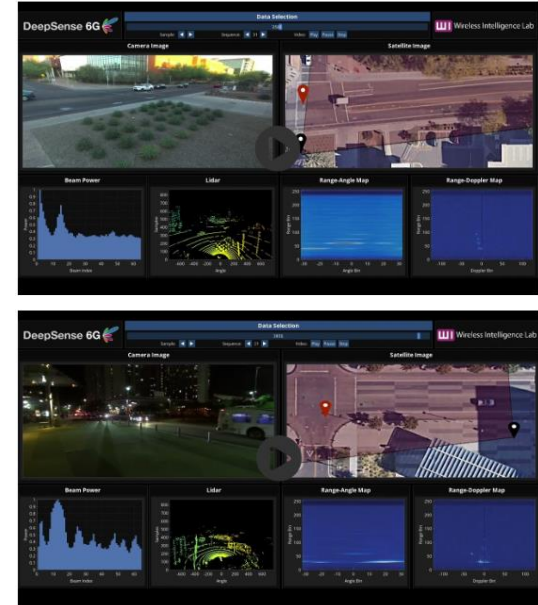
Problem Statement

- Communications beyond 5G
 - High frequency (mmWave) and narrow beams
 - Boost capacity, increase SINR, reduce energy
 - Challenges in mobility and beam management
 - Propagation loss, high speed, high reliability
- Sensing-assisted beam prediction
 - Beam prediction from multi-modality sensors
 - 5-instance camera, LiDAR, radar + 2-instance GPS
 - Predict beam with maximum uplink received power
 - GPS: high latency, energy, interruption issues
 - Sensors: environment (blockage, reflection), location



Problem Statement

- Challenges of sensing for beam prediction
 - Data from different time, location, sampling rate
 - Generalization to unseen scenario than training
 - Fusing 3D LiDAR, radar, 2D camera, 1D GPS data
 - Multiple static and mobile objects without labels
 - Misaligned viewing angles of camera, LiDAR, GPS
- Distance base accuracy of top 3 beams
 - Distance to ground-truth beams
 - $$Y_K = 1 - \frac{1}{N} \sum_{n=1}^N \min_{1 \leq k \leq K} \min \left(\frac{|\hat{y}_{n,k} - y_n|}{5}, 1 \right)$$
 - Adjacent beams serve better connection
 - $|\hat{y}_{n,k} - y_n| \leq 4$



Sensing Data Preprocessing

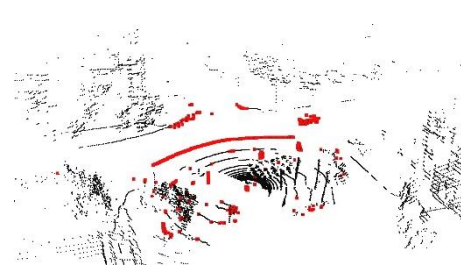
- Camera data:
 - Difficult to recognize targeted user from other mobile agents and backgrounds
 - Enhancing the brightness
 - MIRNet: lighten night scenarios 33, 34
 - Semantic segmentation
 - PDNet: highlight vehicle from background
 - Background masking
 - Blackout background and retain street
 - Guide deep learning model to focus on regions and objects of interests



Sensing Data Preprocessing

- LiDAR data:
 - Bird Eye View (BEV) projection
 - Discretize ROI into grid cells
 - Encode height, intensity per cell
 - Preserve point-cloud structure in 2D
 - Learn with CNN, less computation
 - Custom Field of View (FoV)
 - Crop BEV to align FoV with camera
 - Filtering backgrounds
 - Filter static points by moving average

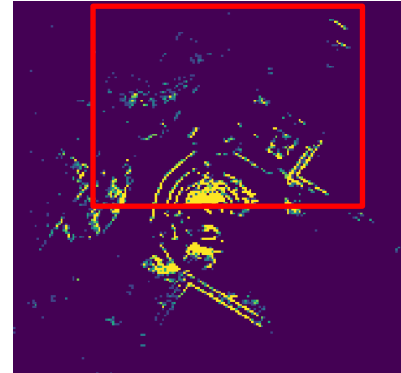
3D Point-Cloud



Bird-Eye-View

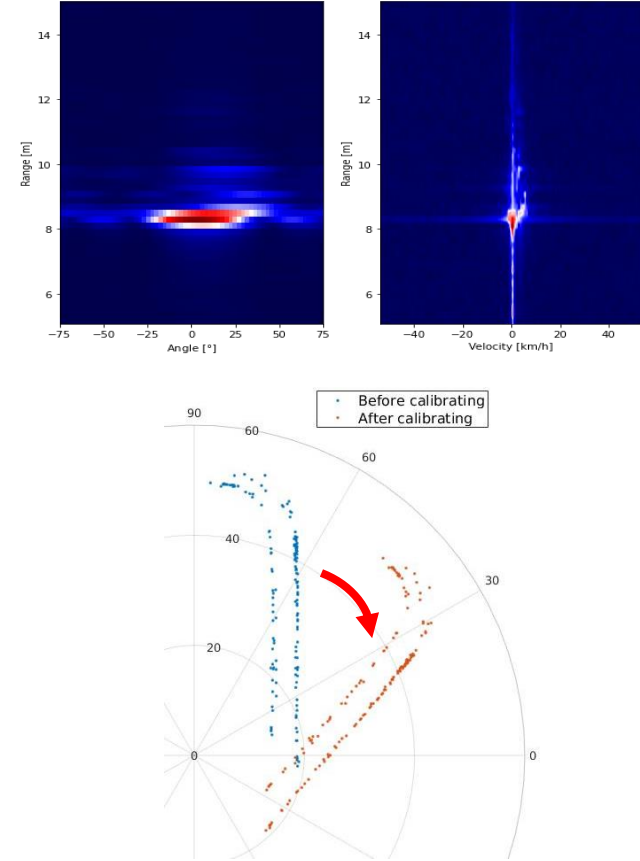


Field-of-View

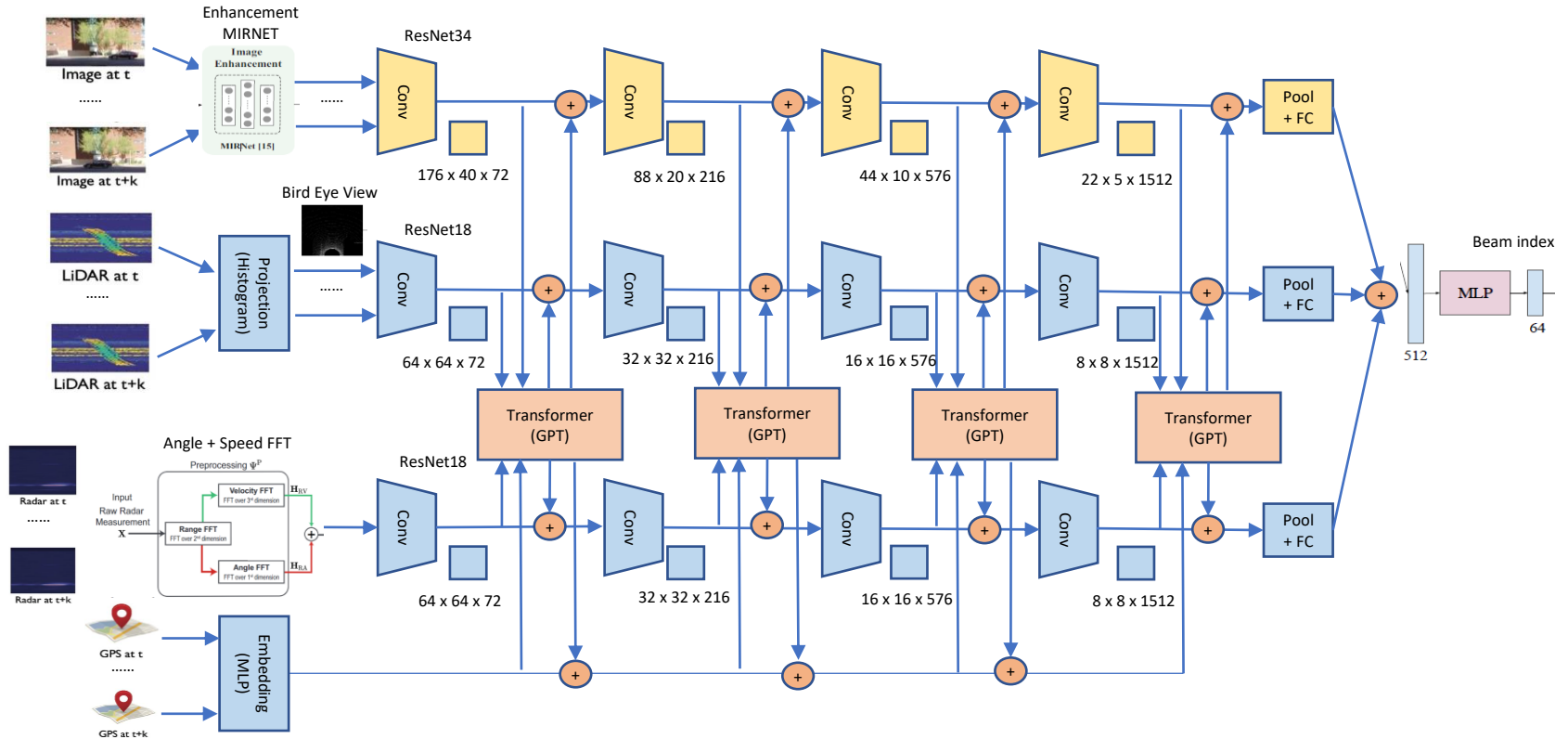


Sensing Data Preprocessing

- Radar data:
 - 2D Fourier transform to produce range-angle and range-velocity maps
 - Reliable speed information without impacts from the environments
- GPS data:
 - Min-max normalization
 - Produce UE relative coordinates ($\Delta x, \Delta y$) with refer to BS and divide maximum value
 - Calibrated angle normalization
 - Position zero-degree coordinate to the central pixel of images in all scenarios



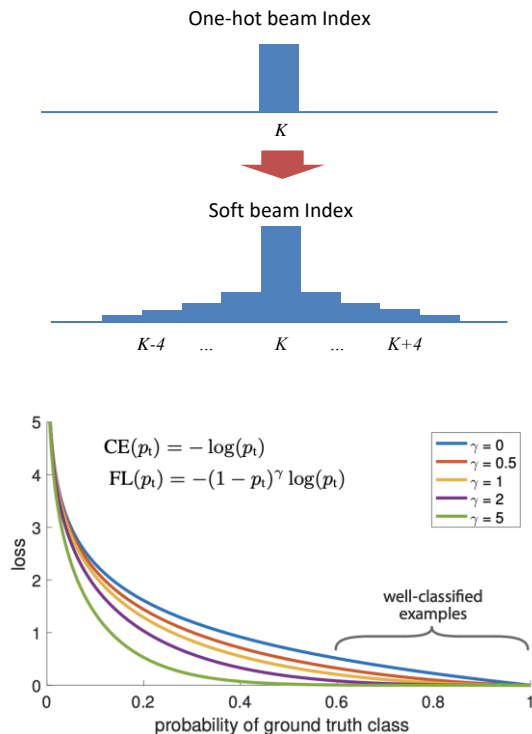
Deep Learning for Beam Prediction



Transformer-based Multi-Modal Sensing assisted Beam Prediction Model

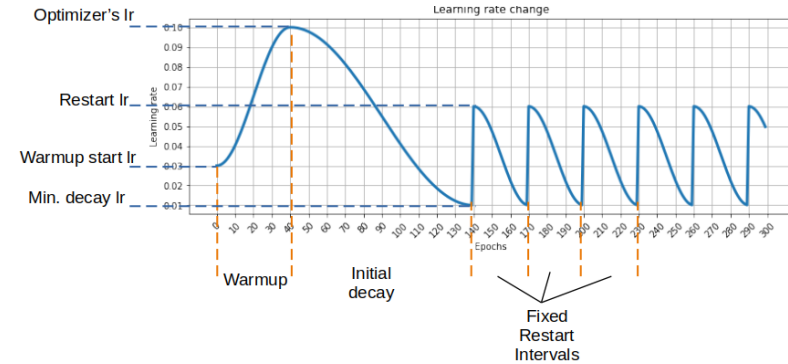
Deep Learning for Beam Prediction

- Soft beam index
 - Change one-hot index to Gaussian distribution
 - Match CE loss function with DBA scores
- Foal loss
 - Modulating factor focus training on hard examples
 - Solve data imbalance between scenarios and class
- Data augmentation
 - Change image brightness, contrast, gamma, hue, saturation, sharpness, blurring
 - Add random noise and downsample LiDAR, radar



Deep Learning for Beam Prediction

- Cyclic cosine decay scheduler
 - Stabilize convergence in training
 - Gradually reduce SGD momentum
- Exponential moving average
 - Improve model robustness
 - Reduce last n step fluctuations



$$\theta_n = \theta_1 - \sum_{i=1}^{n-1} g_i$$



$$\theta_n = \theta_1 - \sum_{i=1}^{n-1} (1 - \alpha^{n-i}) g_i$$

Experimental Results

- Single 5th timestamp
 - High score in trained scenarios
 - Fine tune improves performance
- Multiple timestamps
 - Focal loss reduce imbalance impact
 - GPS angle calibrate improves s31
 - EMA enhance general robustness
 - LiDAR FoV calibrate perform best

TABLE I: DBA score on test dataset of developed schemes

Test	Base	Enhance	Overall	31	32	33	34
A		Timestamp 5 Image enhance Radar angle	0.4618	0.1147	0.6864	0.7848	0.8188
B	A	Fine tune 31	0.5891	0.4718↑	0.6222	0.6933	0.7328
C	A	Timestamp 1 to 5 Radar velocity Focal loss Cosine decay LR Soft beam index	0.5989	0.4509	0.6852↑	0.7538↑	0.7369
D	C	GPS angle norm Data augment	0.5997	0.4713↑	0.7000	0.7424	0.6997
E	D	EMA	0.6325	0.4760	0.7123	0.7819↑	0.7985↑
F	D	LiDAR FoV	0.6671	0.5331↑	0.7173	0.7910↑	0.8209↑

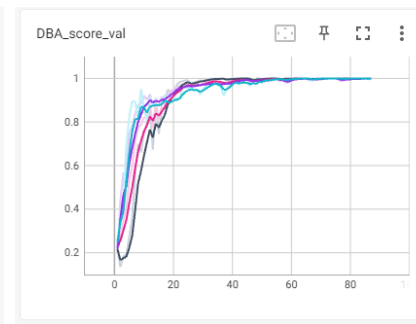
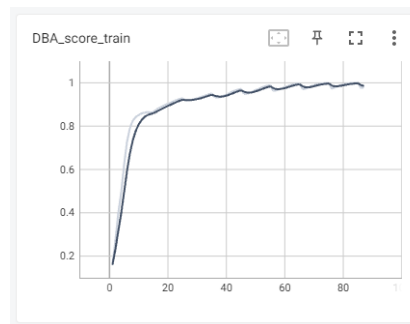
Experimental Results

- Background reduction
 - Reduced score when filter, mask and segment on LiDAR and image
 - Visual sensing provide gain from environment information
- Convergence performance
 - Converges at 80 epochs, in all datasets and scenarios
 - EMA reduce fluctuation impacts

TABLE II: DBA score on test dataset of experimental preprocessing

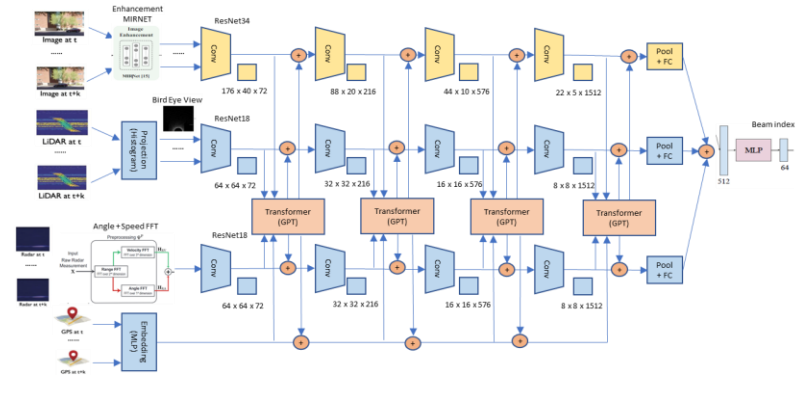
Test	Base	Enhance	Overall	31	32	33	34
G	F	LiDAR filter	0.6398	0.4856	0.7000	0.7914	0.8061
H	G	EMA	0.6458	0.5347	0.6951	0.7505	0.7679
I*	F	Image segment Image mask	0.6298	0.4709	0.7284	0.7810	0.7684
J*	I	EMA	0.6433	0.4947	0.7506	0.7890	0.7837

* No image enhancement in scenario 33 and 34.



Conclusion

- Contribution
 - Transformer deep learning for beam prediction
 - Preprocess sequential multi-modal sensor data
 - Generalize to various scenario and applications
- Advantage
 - Tailorable model size, data sequences, modalities
 - Robust in extreme environments: fog, rain, cloud
 - Diverse devices and sensors in wireless network
- Enhancement
 - Contrastive learning improve generalization
 - Semi-supervise learning reduce labeling needs
 - Feature learning improve multi-modal abstraction



- Extension
 - Beam, power, resource management, RIS
 - Sensing, localization, trajectory prediction
 - Collaborative control vehicle, robot, traffic

Thank you