Radar Image Reconstruction from Raw ADC Data using a Parametric Variational Autoencoder with Domain Adaptation

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Introduction

Goal:
Localization of human targets in indoor environment using a low-cost radar sensor.

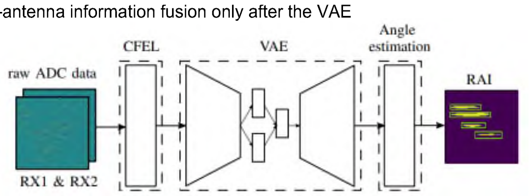
Challenges:
Indoor environment → occlusions, ghost targets, multipath reflections, etc.
Limited training data

Contribution:
Single-frame human position estimation from the raw ADC data with a variational autoencoder and domain adaption to overcome the limited training data

Architecture – Proposed Solution

Proposed Solution:

- Localization via a variational autoencoder
- Parametric layer for FFT sampling learned through proposed CFEL
- Domain adaptation using synthetic data
- Cross-antenna information fusion only after the VAE

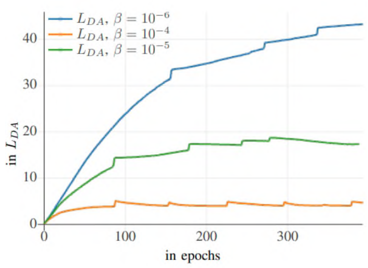


$$loss = L_{FL} + \beta \cdot L_{DA} + \phi \cdot L_{KL}$$

Focal Loss | Domain Adaptation | KL-Divergence

Domain Adaptation

- To overcome limited real world dataset we use domain adaptation
- Source domain: Synthetic data generated by Matlab
- Target domain: Real sensor recordings
- Pretrain especially angle estimation
- Using weight difference regularization as loss term
- The image shows the loss divergence depending on the influence of the difference regularization to the over-all loss term

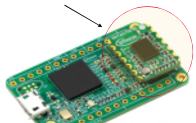


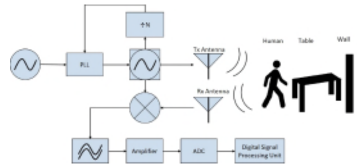
$$L_{DA} = \sum_{i \in T} \frac{||w_i - w_{i0}||^2 + ||b_i - b_{i0}||^2}{||w_{i0}||^2 + ||b_{i0}||^2}$$

T : set of convolutional layers
Y : target domain, S : source domain
$\omega_i \in$ Y, $\omega_{i0} \in S$

Traditional Pipeline

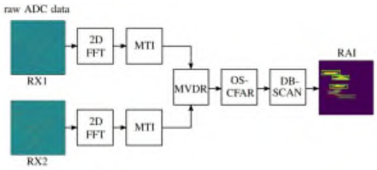
Radar sensor





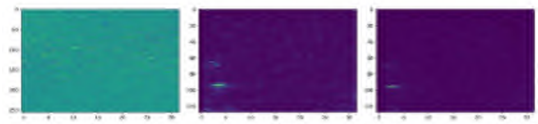
Traditional processing:

- FFTs + MTI → Range Doppler Images
- MVDR beamformer → angle estimation
- OS-CFAR → possible target detection
- DB-SCAN → ghost target rejection



Complex Frequency Extraction Layer

- Parametric layer → filter kernels are defined by a finite set of parameter
- Filter kernels are complex frequencies in slow- and fast-time
- Set of parameter are the frequencies in slow- and fast-time
- Therefore the CFEL acts as trainable 2D DFT that mimics the 2D FFT pre-processing
- The image shows (a) the raw time-domain data, (b) the range-Doppler image generated by a common 2D FFT and (c) the feature map of the proposed CFEL



(a) Time domain data (b) RDI (c) Features after CFEL

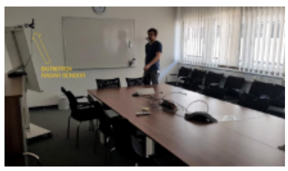
Dataset

Synthetic Dataset:

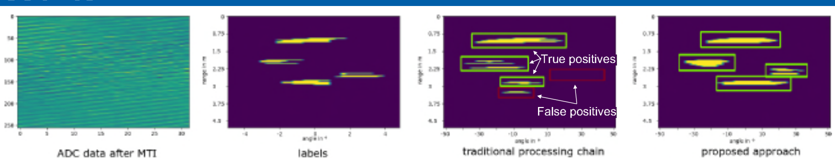
- Reflections from point targets are simulated for all discretized range-angle bins using Matlab's phased array toolbox

Human Target Dataset:

- Measurements with one real moving target in a typical conference room
- Two to four target measurements created via superposition of one target measurements
- Some augmentation by shifting the one target measurements in range via multiplication with different complex exponentials



Results



- Clear improvement over traditional 1-frame localization
- Slightly better performance than other autoencoder-based approach in [1], with better performance on general point target angle estimation

Approach	Description	F1-Score	Model Size
Traditional	OS-CFAR with DBSCAN	0.61	-
AE	AE with complex RDI as input	0.77	1.23 MB
VAE	VAE with CFEL layer and DA	**0.80**	1.71 MB

References

[1] M. Stephan, A. Santra, and G. Fischer, Human Target Detection and Localization with Radars using Deep Learning. Springer, 2020.

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