Automotive Radar Image Segmentation with Frame Fusion

Yang Xiao, Liam Daniel, Scott Cassidy, Sukhjit Pooni, Edward Hoare, Anum Ahmed Pirkani, Mikhail Cherniakov, and Marina Gashinova

<u>Presenter: Anum Ahmed Pirkani</u>

Affiliation: Microwave Integrated Systems Laboratory (MISL), The University of Birmingham, UK

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Motivation of Frame Fusion on Automotive Image Segmentation

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Frame fusion of automotive radar image segmentation

Previous work shows good potential for image segmentation of automotive radar imagery in the single radar frame. → Improve the performance by fusing information from several consecutive frames.

Image segmentation on automotive radar maps

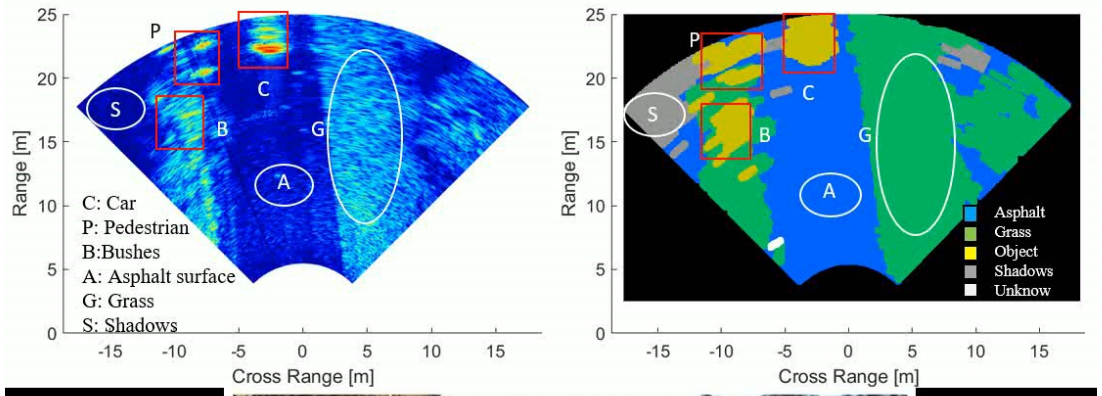
Utilize mm-wave and sub-THz radar → Allows high resolution and high sensitivity automotive radar imagery → Provide imagery for full deep scene reconstruction

Image segmentation

Segment image and classify the surfaces and objects → Identify the passable region → Autonomous path planning and obstacle avoidance

Instances of single frame segmentation

Automotive radar map | **Segmented radar map**



Segmented optical imagery using Mask-RCNN

Single Frame Image Segmentation Overview

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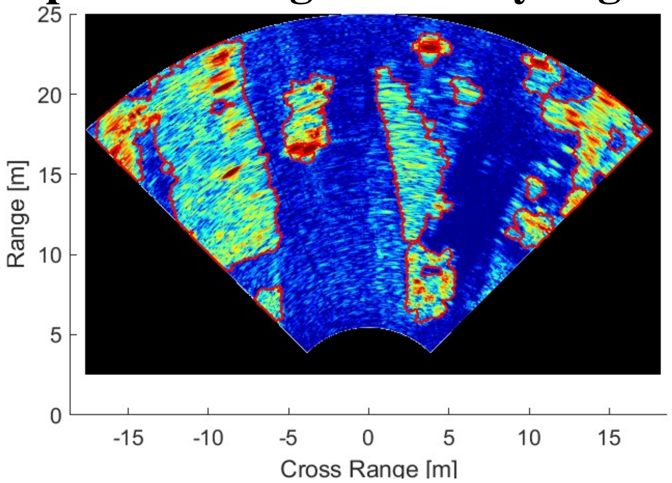
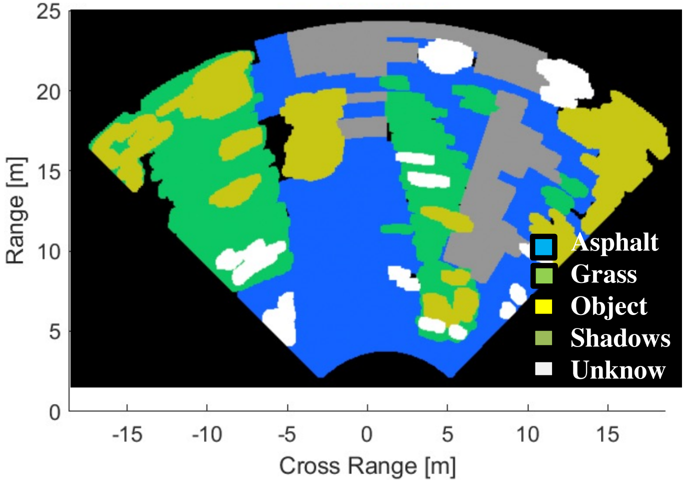
Image ROI creation for the classifier has been accomplished using the Canny edge detection

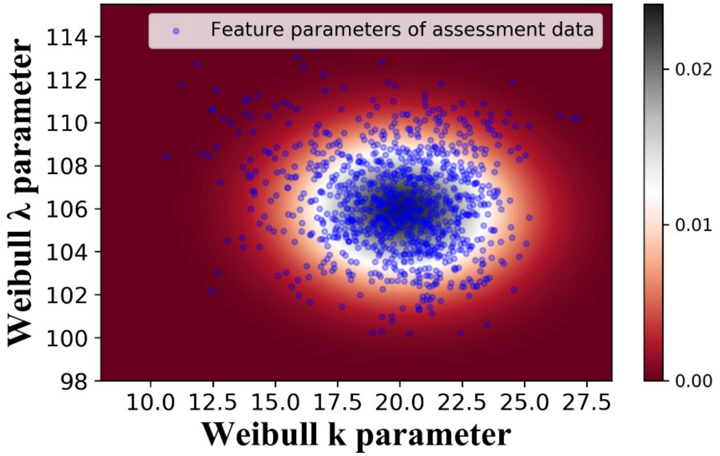




Segmented radar map after region classification using MGD classifier.

MGD classifier in [1]

Example: Bi-variate Gaussian PDF for Asphalt



Supervised classification method using the MGD model

- Distribution features are the variates

Classifier trained using distribution features to form estimates of the mean vector and covariance matrix

- One MGD is trained per class

Input test vector of features into each class MGD

- Obtain probability that the test data belongs to each class

Remaining problem of single frame segmentation: The unknown areas (white labeled) are produced as they have low feature bias to any of the considered classes.

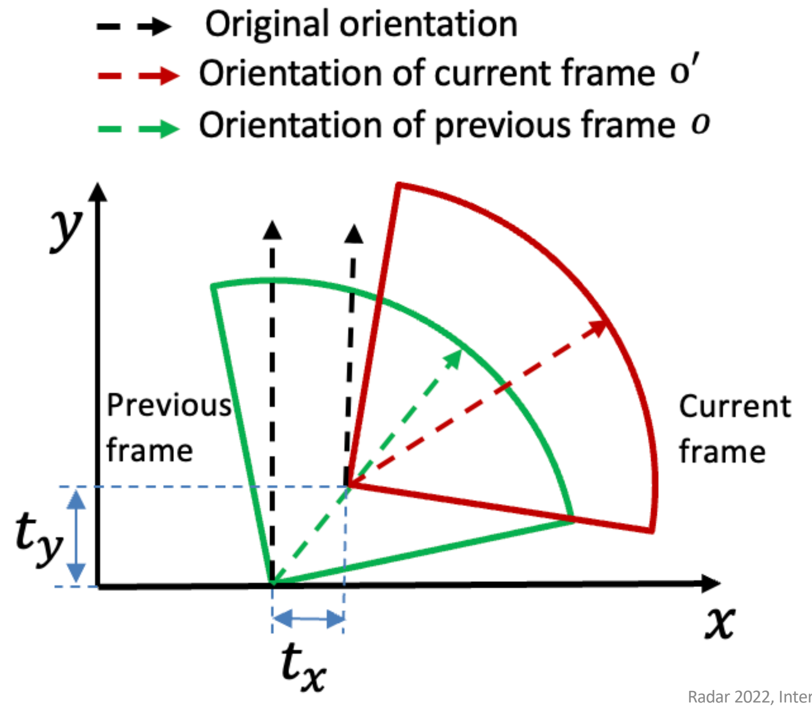
[1]Y. Xiao, L. Daniel and M. Gashinova, "Image Segmentation and Region Classification in Automotive High-Resolution Radar Imagery," in *IEEE Sensors Journal*, vol. 21, no. 5, pp. 6698-6711, 1 March1, 2021, doi: 10.1109/JSEN.2020.3043586.

Geometric Transformation of Frame Registration

The geometric transformation between radar maps

$$\begin{cases} x' = s_x \cos(\theta) x - sh_x \sin(\theta) y + t_x \\ y' = sh_x \sin(\theta) x + s_y \cos(\theta) y + t_y \end{cases}$$

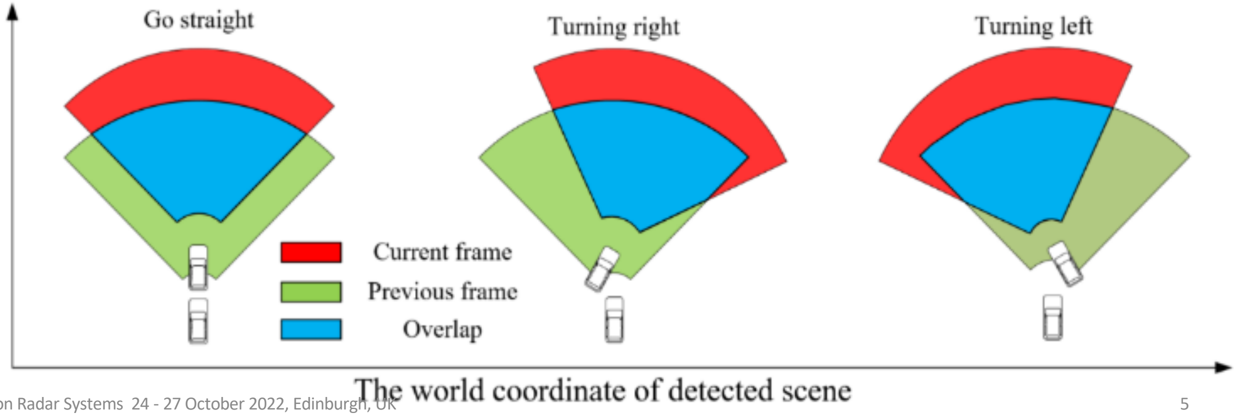
The representation of orientation and shifts



The notification of related parameters

- (x, y), (x', y'): coordinates in previous and current radar frame;
- Constant parameters:
- ❑ s_x, s_y: scale factors (assumed as '1' in radar map registration);
- ❑ sh_x, sh_y: shear factors (assumed as '1' in radar map registration);
- Parameters obtained by IMU:
- ➢ $\theta = o' - o$ is the rotation angle, o' and o are the orientations of current and previous frames.
- ➢ t_x and t_y are the position shifts.

The layout of three driving scenarios



IMU Measurement of Frame Registration

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The output of the IMU setup

- Precise GPS information which includes latitude lat , longitude lon and height hei.
- The real-time driving information which includes velocity v, angular velocity ω, acceleration a and orientations o' and o .

The procedure of calculating the position shifts using IMU

Represent the cartesian coordinate of the vehicle in current frame (x_c, y_c) and previous frame (x_c', y_c') ($R = 6371$ m is the approximate radius of the earth):

$$\begin{cases} x_c = R \cdot \cos(lat) \cdot \cos(lon) \\ y_c = R \cdot \cos(lat) \cdot \sin(lon) \end{cases}$$

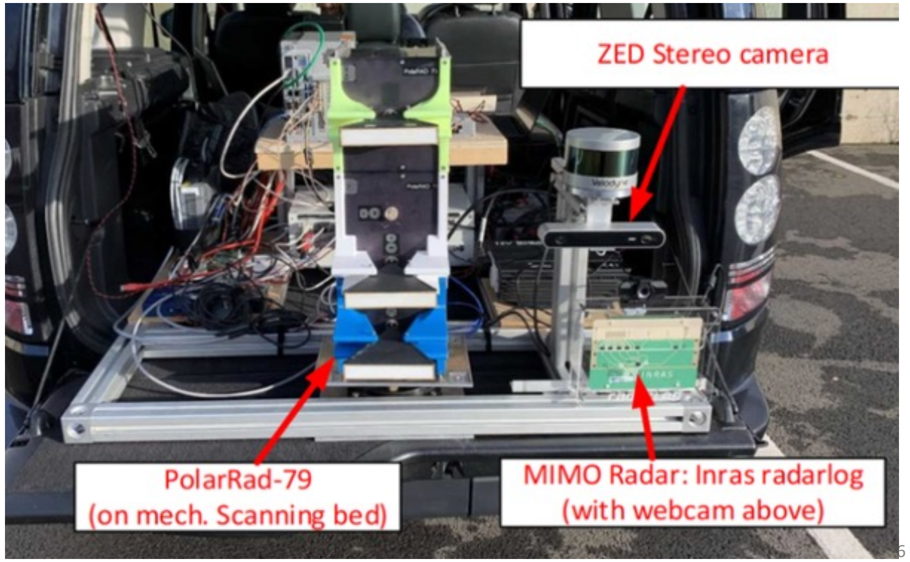
Calculate the position shifts t_x and t_y:

$$\begin{cases} t_x = x_c - x_c' \\ t_y = y_c - y_c' \end{cases}$$

Calculate the geometric transformation between frames:

$$\begin{cases} x' = s_x \cos(\theta) x - sh_x \sin(\theta) y + t_x \\ y' = sh_x \sin(\theta) x + s_y \cos(\theta) y + t_y \end{cases}$$

(a) The installation of IMU setup



(b) The installation of radar systems

Frame Registration of Automotive Radar Imagery using IMU

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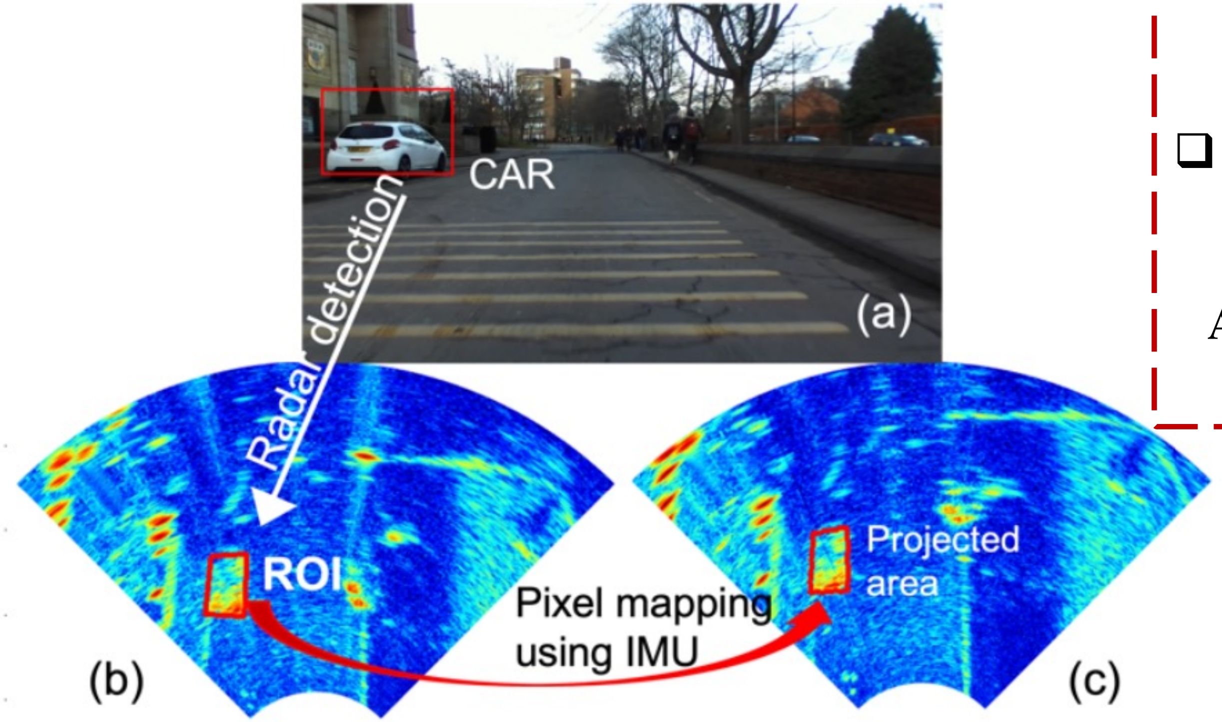
(a) The optical image



(b) The previous frame with ROI

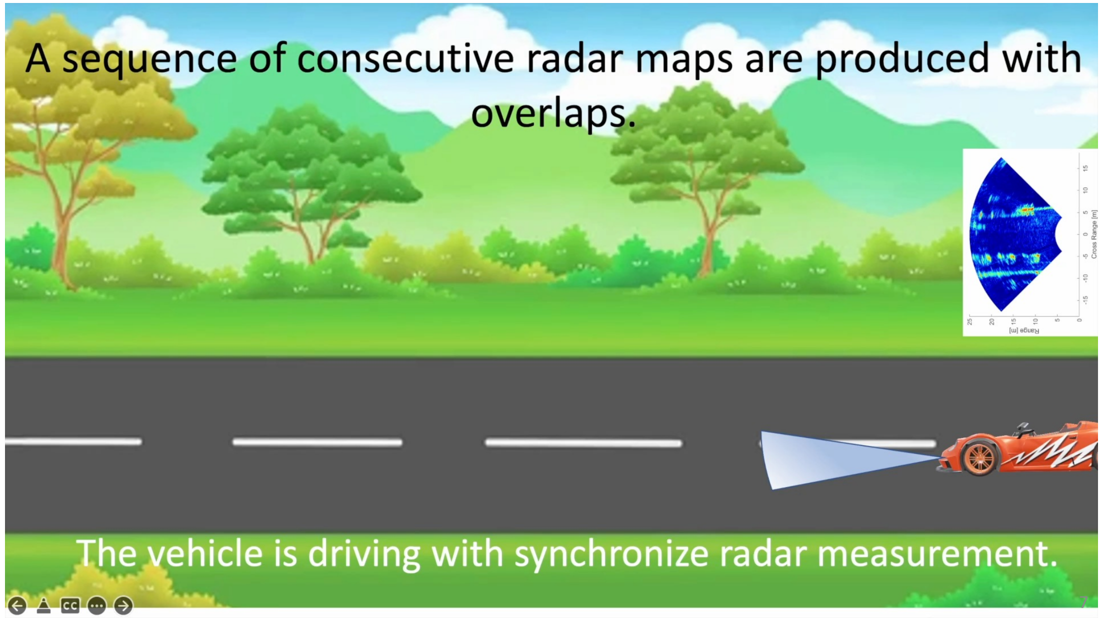
(c) The current frame with projected area

The pixel mapping of two consecutive radar maps on stationary car as the instance.

Frame registration:

- In the instance, the stationary car which is highlighted by the red bounding box in the frame of (b), is to be projected into the next frame (c).
- The projected area coincides well with the position of the car in the consecutive frame.

All overlap regions in the seed frame will be projected to the next consecutive frames using frame registration.



Frame Fusion based on Kalman Filter

Kalman filter:
- Estimate the current system state based on previous and current measurements.
- In our application, utilized to mitigate the error caused by the feature variation of radar frames by considering the classification information of multiple frames.

The definition of Kalman Filter method based on our application

$$\boldsymbol{x}_{n,n}=\boldsymbol{x}_{n\text{-}1,n}+\boldsymbol{x}_{n\text{-}2,n}+\boldsymbol{x}_{n\text{-}3,n}+\boldsymbol{u}_n$$

- $\hat{\boldsymbol{x}}_{n,n}$: predicted weights for the classification of current frame (CF);
- $\hat{\boldsymbol{x}}_{n-1,n}$, $\hat{\boldsymbol{x}}_{n-2,n}$, $\hat{\boldsymbol{x}}_{n-3,n}$: classification weights obtained based on the classification results of previous frames (PFs);
- $\boldsymbol{u}_n$: the weights obtained from the output of MGD classifier in the single frame segmentation of CF.

Calculation of $\hat{\boldsymbol{x}}_{n-1,n}, \hat{\boldsymbol{x}}_{n-2,n}, \hat{\boldsymbol{x}}_{n-3,n}$

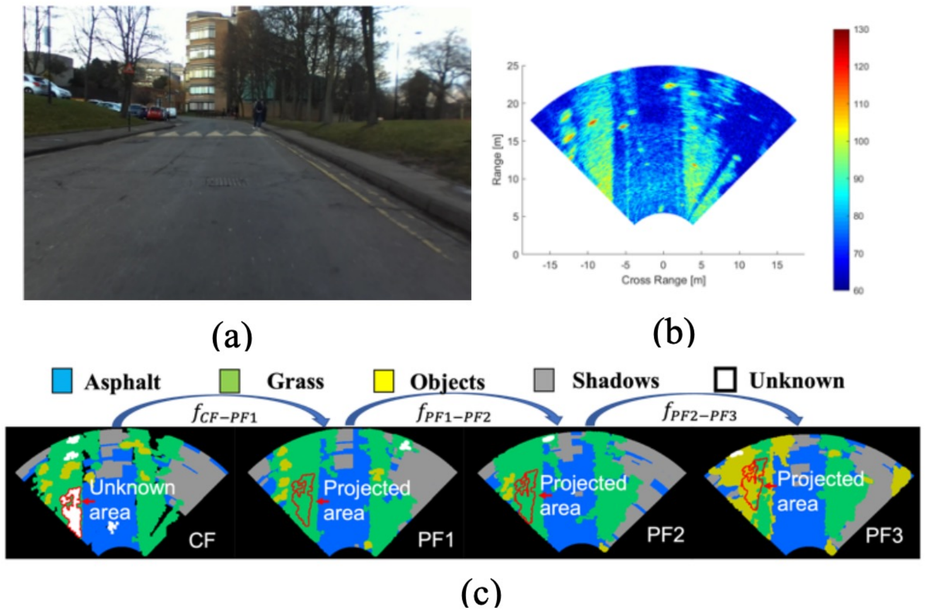
Geometric transformation:

$$\begin{cases} C_{PF1} = f_{CF-PF1}(C_{CF}) \\ C_{PF2} = f_{PF1-PF2}(C_{PF1}) \\ C_{PF3} = f_{PF2-PF3}(C_{PF2}) \end{cases}$$

Class weight calculation:

- Region class weights obtained from PF*x*: $\hat{x}_{n-x,n} = [p_a^{PFx}, p_g^{PFx}, p_s^{PFx}, p_o^{PFx}]$
- Each item is calculated as: $p_i^{PFx} = \dfrac{N_i}{N_s}$

(a) optical image (b) radar map

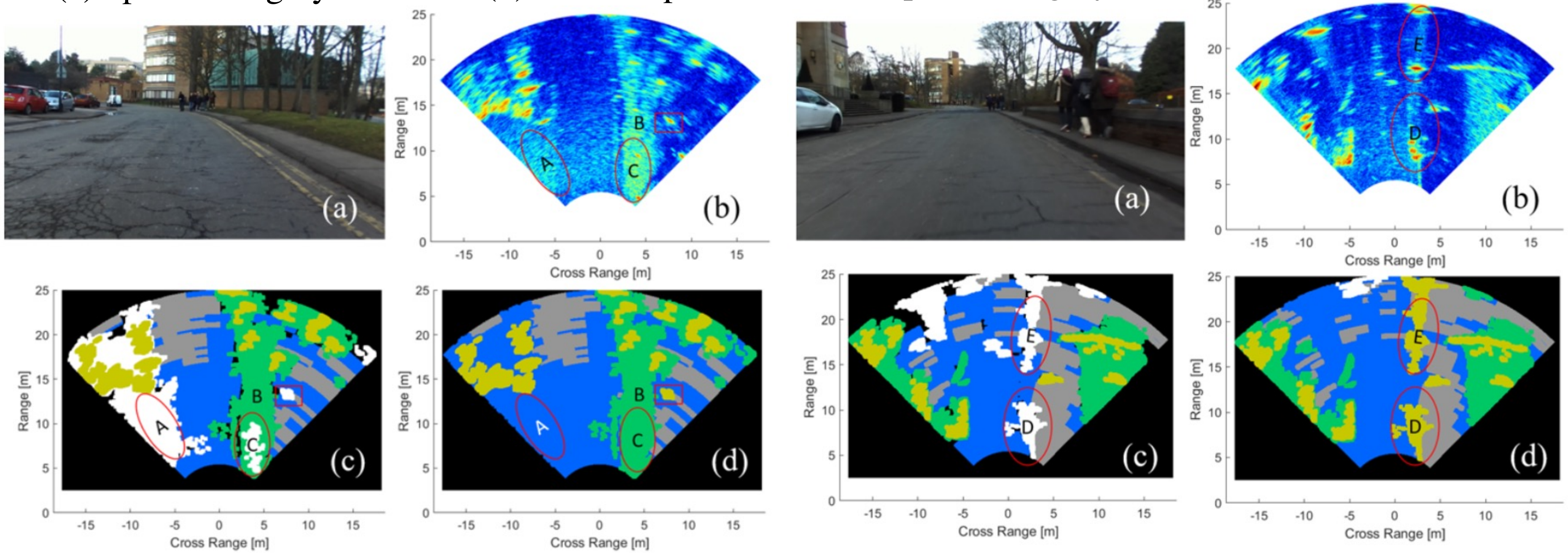


(c) tracking of the unknown areas

Example of the identification of unknown area using frame fusion

Results of Frame Fusion on Automotive Radar Map Segmentation

(a) optical imagery (b) radar map (a) optical imagery (b) radar map



(c) Single frame segmentation (d) Frame fusion segmentation (c) Single frame segmentation (d) Frame fusion segmentation

Jaccard Similarity Co-efficient Estimation

The comparison of JSCs before and after frame fusion implementation

Area classes	Asphalt	Grass	Objects	Shadows
JSCs of single frame	0.69	0.7	0.68	0.83
JSCs after frame fusion	0.77	0.86	0.72	0.83

$$J_{class} = \frac{A_{fs} \cap A_{label}}{A_{label}}$$

A_{fs} is the correctly classified pixels; A_{label} is the labeled pixels.

Conclusions and Future Work

- The frame fusion technique on consecutive radar maps is first time proposed for improving the segmentation of automotive radar maps.
- The proposed frame fusion method includes two stages:
  1) the pixel mapping between consecutive frames based on the IMU measurement;
  2) the information fusion of multiple frames using Kalman filter.
- The frame fusion results show significant improvement on the segmentation performance compared with the results obtained by single frame segmentation.
- The proposed segmentation with frame fusion is applicable to various high-resolution consecutive automotive radar imagery.

Future work: tracking on moving objects.