RFCM FOR DATA ASSOCIATION AND MULTITARGET TRACKING USING 3D RADAR

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Introduction

- Propose regularized FCM (RFCM) method for solving the data association uncertainty problem in Multitarget Tracking for the 3D 79 GHz radar
- Proposed method alleviates data association uncertainty problem by taking the interaction between targets into account

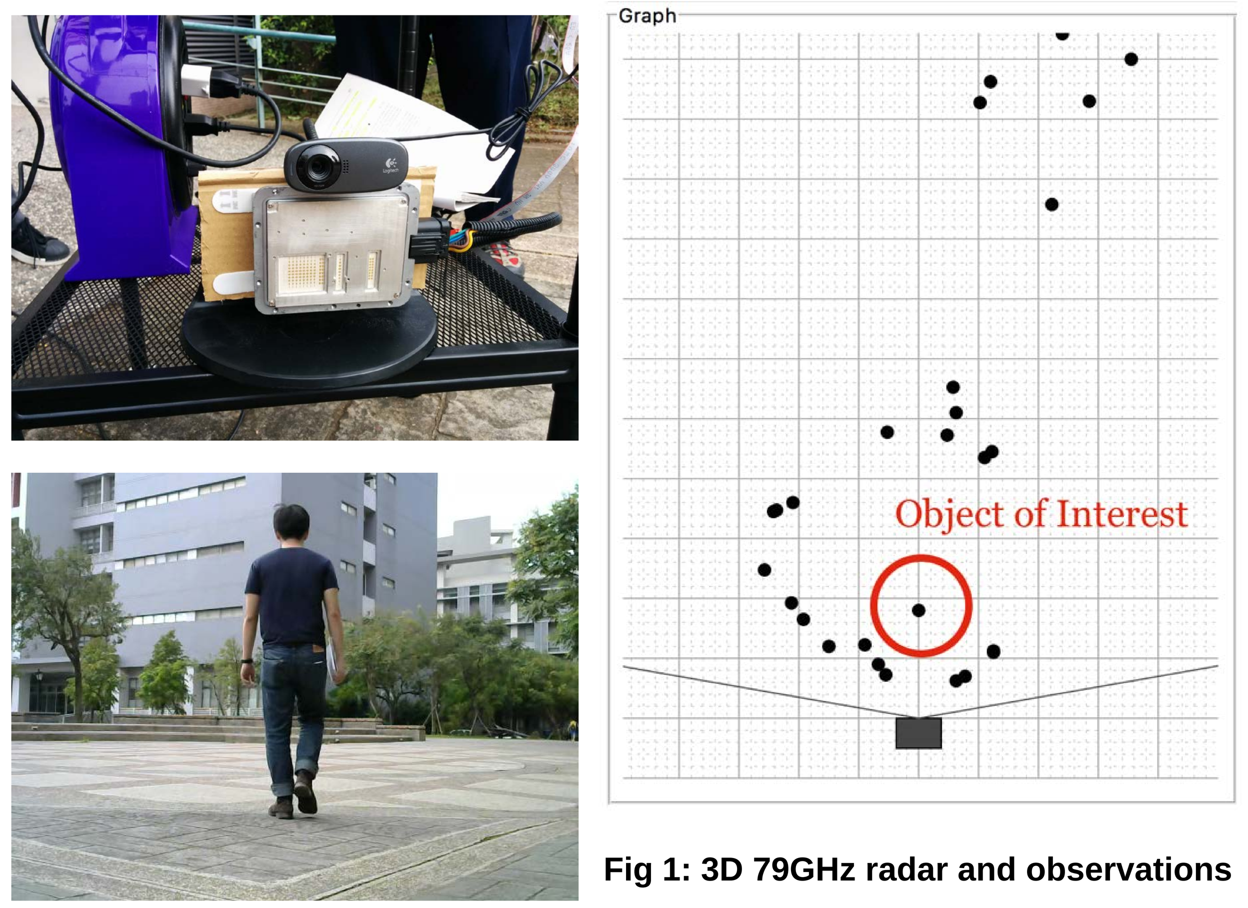

Fig 1: 3D 79GHz radar and observations

Methods - Tracking with FCM

1. Use the DBSCAN clustering algorithm to determine the initial cluster for cycle t using $x_j, y_j, v_{x,i}$ and $v_{y,i}$ for $i = 1, \ldots, n$ as features to obtain C number of centroids. N denotes the data point index
2. Use the resulting centroids $\hat{\mathbf{c}}_i(t) \triangleq [x_i \quad y_i \quad v_{x,i} \quad v_{y,i}]^T$, for $i = 1, \ldots, C$ as state and observation vector to the EKF to obtain the predicted centroid for C centroids, denoted as $\mathbf{c}_i^p(t) \triangleq \left[x_j^p \quad y_j^p \quad v_{x,j}^p \quad v_{y,j}^p\right]^T$
3. Use $\left[x_j^p \quad y_j^p\right]^T$ as initial centroid for the FCM algorithm to find the centroid for the next cycle $t_0 + 1$, denote as $\hat{\mathbf{c}}_i(t+1)$
4. $\hat{\mathbf{c}}_i(t+1) \rightarrow \hat{\mathbf{c}}_i(t)$, go to Step 2) and repeat until features from all cycles are processed

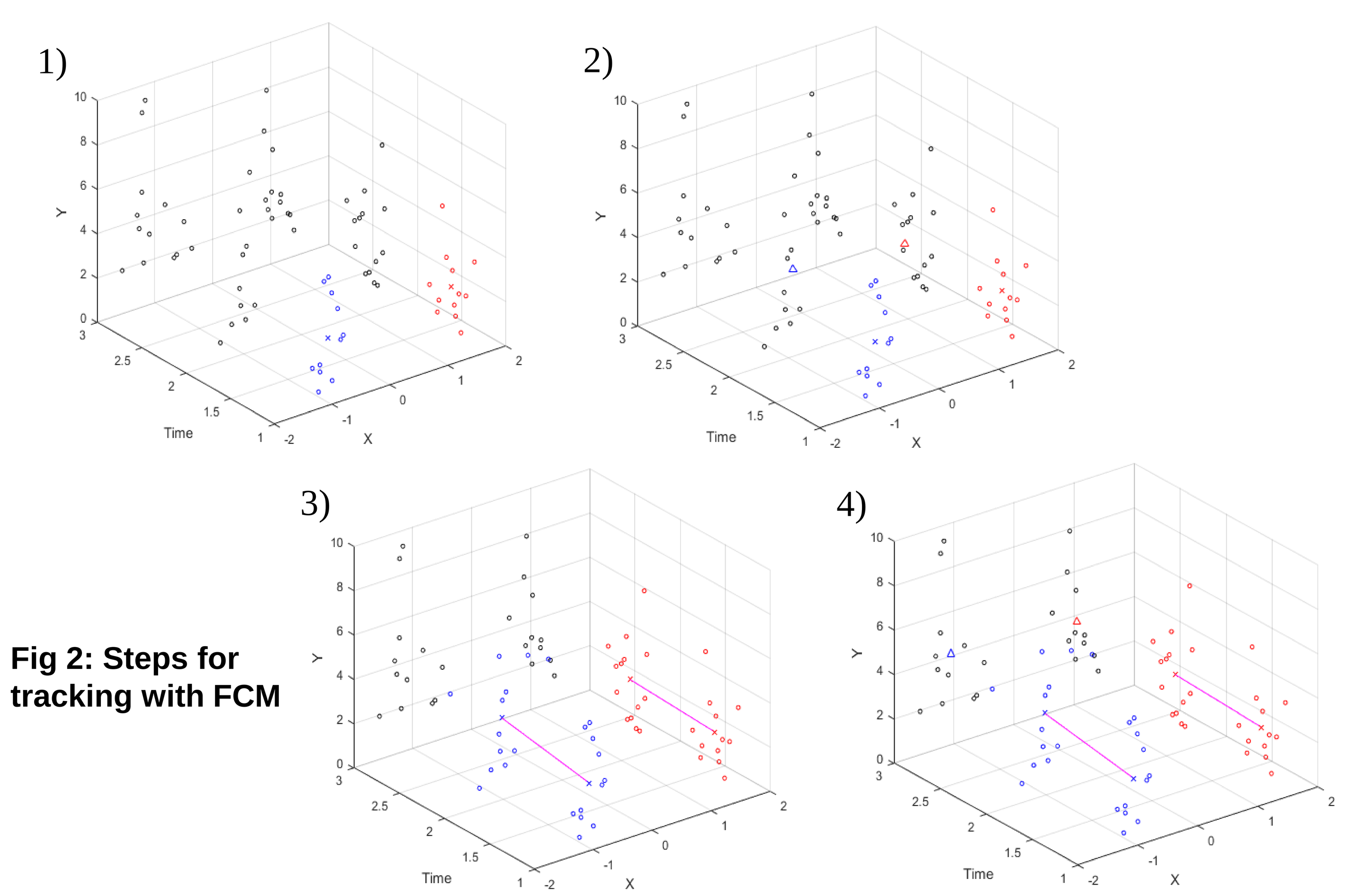

Fig 2: Steps for tracking with FCM

Methods - Regularized FCM

$$\min_{\mathbf{c}_i} \sum_{j=1}^{N}\left(\sum_{i=1}^{C} u_{i,j}^m d_{i,j}^2 + \frac{f_1}{C-1}\sum_{\substack{k=1\\k\neq i}}^{C}\frac{\left\|\mathbf{c}_i-\mathbf{c}_k^p\right\|_2^2}{\left\|\mathbf{c}_i^p-\mathbf{c}_k^p\right\|_2^2} + f_2(d_i)\left\|\mathbf{c}_i-\mathbf{c}_i^p\right\|_2^2\right)$$

- $d_{i,j}^2 \triangleq \left\|\mathbf{x}_j - \mathbf{c}_i\right\|_2^2$
- $\mathbf{c}_i^p$ and $\mathbf{c}_k^p$ are the cluster centroid for the i_{th} and k_{th} object
- Two regularization terms offer robustness in case the observations of different targets are noisy or close to each other and overlapped
- Unfortunately, problem is a non-convex

Reformulation

$$\min_{\mathbf{c}_i} \sum_{j=1}^{N}\left(\sum_{i=1}^{C} u_{i,j}^m d_{i,j}^2 + \frac{f_1}{C-1}\sum_{\substack{k=1\\k\neq i}}^{C}\frac{\left\|\mathbf{c}_i-\mathbf{c}_{i,k}^p\right\|_2^2}{\left\|\mathbf{c}_i^p-\mathbf{c}_k^p\right\|_2^2} + f_2(d_i)\left\|\mathbf{c}_i-\mathbf{c}_i^p\right\|_2^2\right)$$

- $\mathbf{c}_{i,k}^p = \left(\mathbf{c}_i^p - \mathbf{c}_k^p\right) + \mathbf{c}_i^p$, the mirror point of $\mathbf{c}_k^p$ with respect to $\mathbf{c}_i^p$

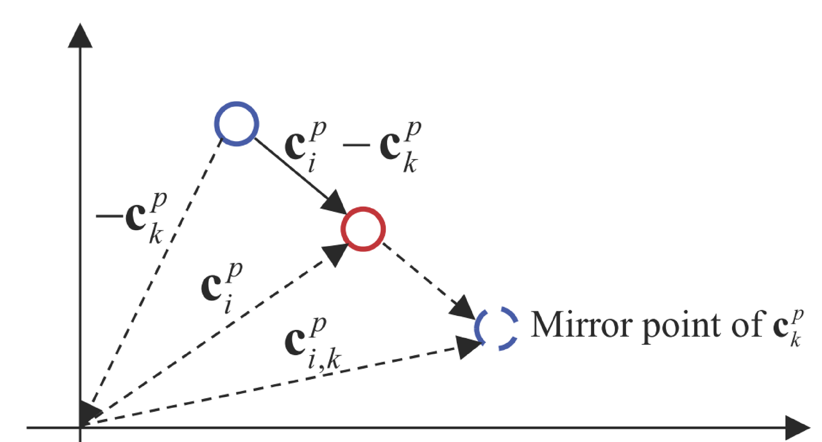

Fig 3: Mirror point $\mathbf{c}_{i,k}^p$ of $\mathbf{c}_k^p$ with respect to $\mathbf{c}_i^p$ (the mirror)

Second Regularization Term

- Design $\hat{\mathbf{c}}_i$ such that it is not close to $\mathbf{c}_k^p$
- f_1 is chosen to be a constant that needs to be manually tuned

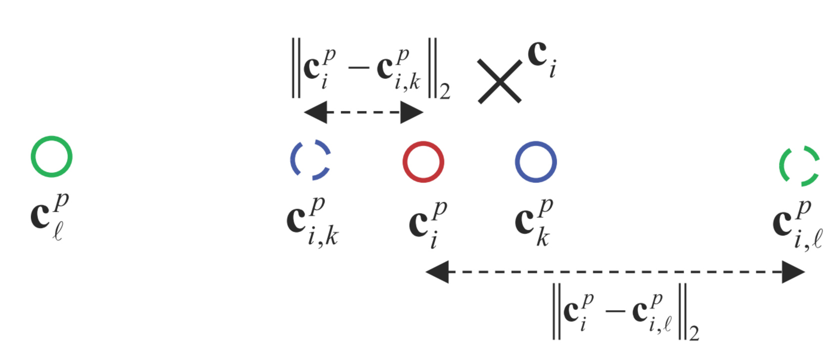

Fig 4: Influence of $\left\|c_i - c_{i,k}^p\right\|_2$ and $\left\|c_i - c_{i,\ell}^p\right\|_2$

Third Regularization Term

- Allows $\hat{\mathbf{c}}_i$ to be attracted to $\mathbf{c}_i^p$, that is, favoring the result from the EKF
- $f_2(d_i) = \alpha \cdot d_i$, with α being a parameter that also requires fine tuning

Results - Simulated Data

- Two objects initially located at $y = 0$ moving away from radar
- Paths of objects follow the shape of cosine function
- Closest to each other at cycle number(time) 415
- The MSE of cycle t is computed as $\mathrm{MSE}(t) = \frac{1}{M}\sum_{m=1}^{M}\sum_{i=1}^{C}\left\|\mathrm{b}_{i(t)} -\right.$

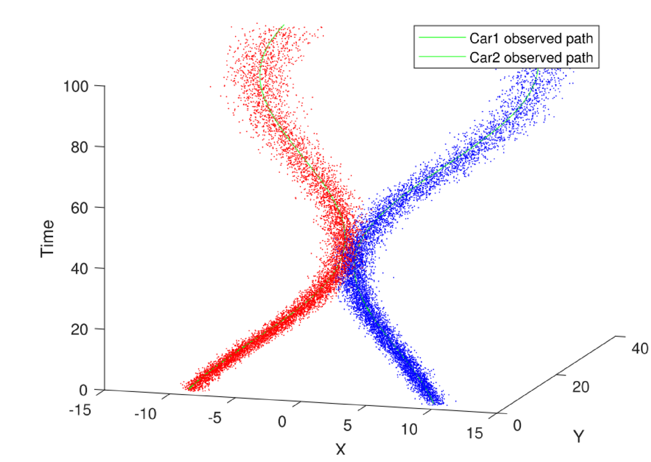

Fig 5(a): Simulated point clouds of two different objects

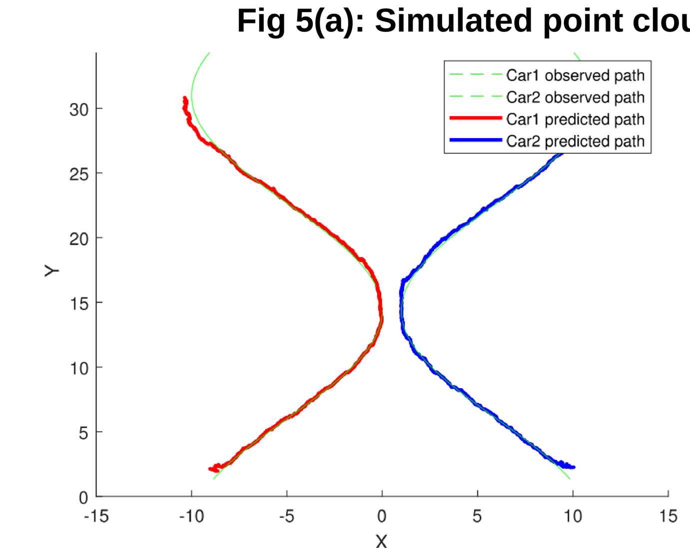

Fig 5(b): FCM for data shown in Fig. 4(a)

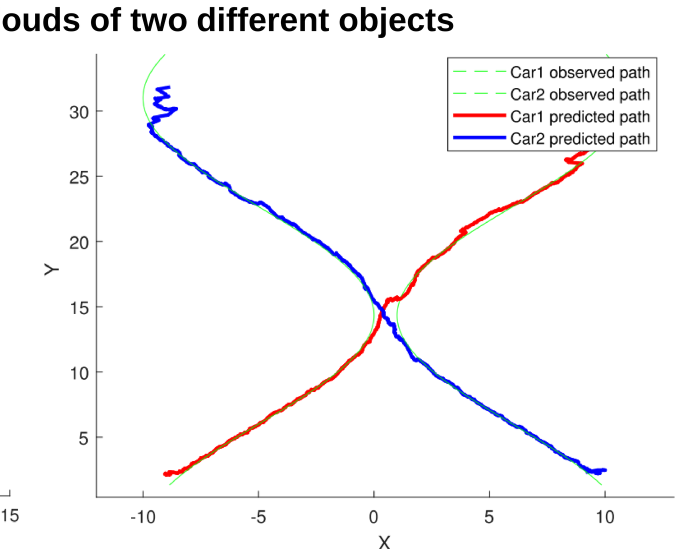

Fig 5(c): RFCM for data shown in Fig. 4(a)

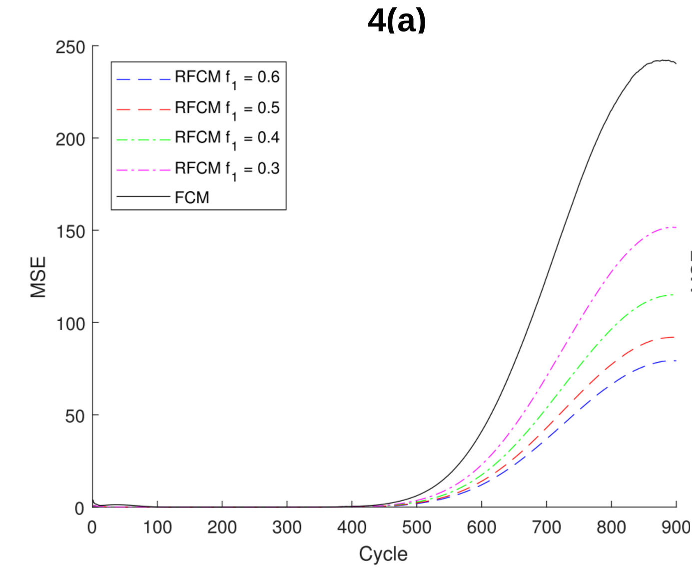

Fig 6(a): MSE vs. cycle time for FCM and RFCM with $\alpha = 0.003$

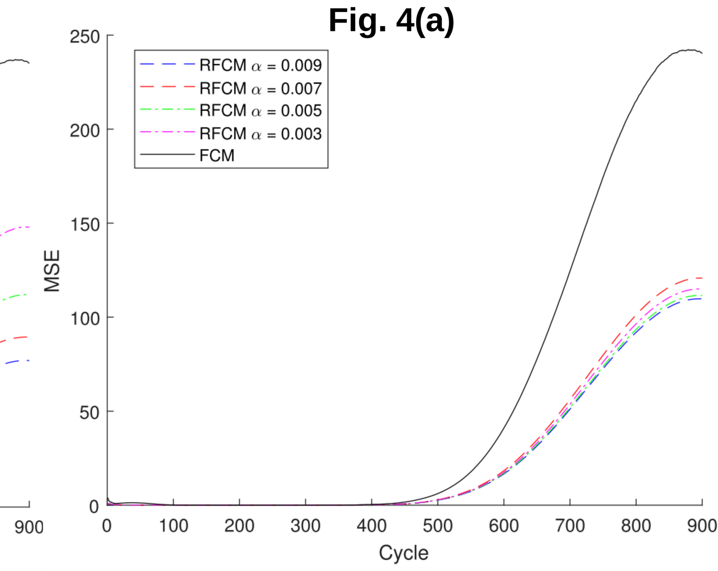

Fig 6(b): MSE vs. cycle time for FCM and RFCM with $f_1 = 0.4$

Results - Field Data

- A pedestrian and a car move side by side away from radar
- Numerous tracks are in the field data because of reflected signal from non-object-of-interest

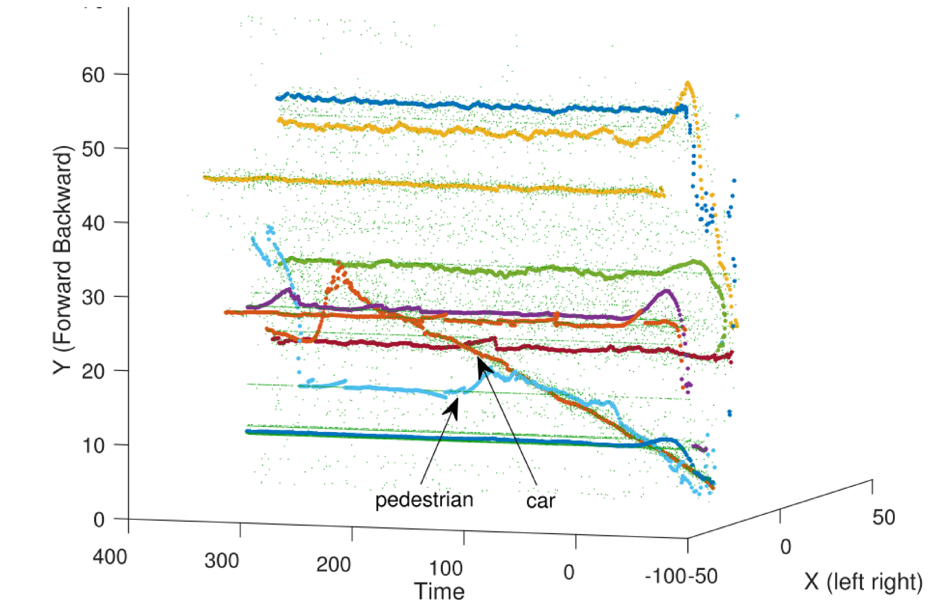

Fig 7(a): FCM for actual field data

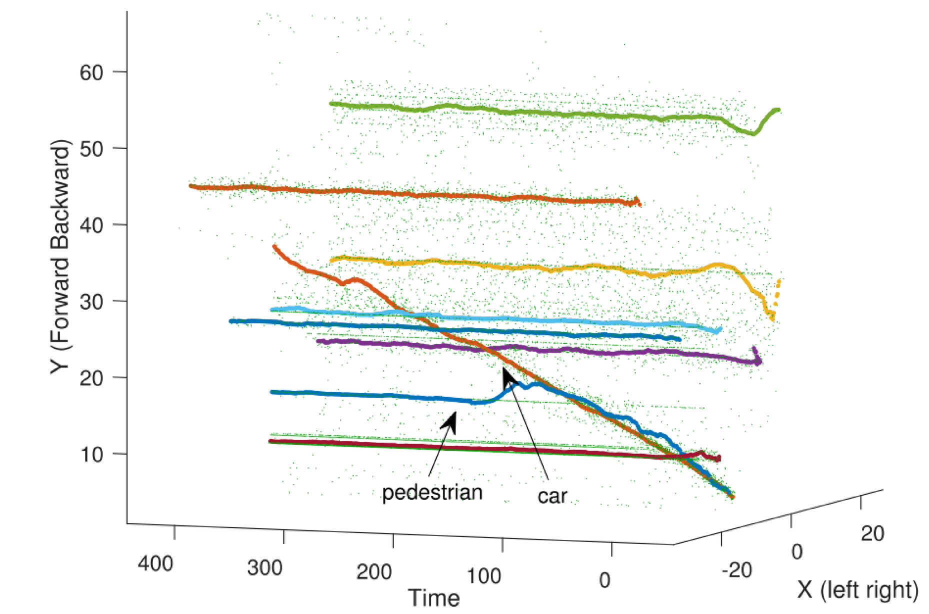

Fig 7(b): RFCM for actual field data

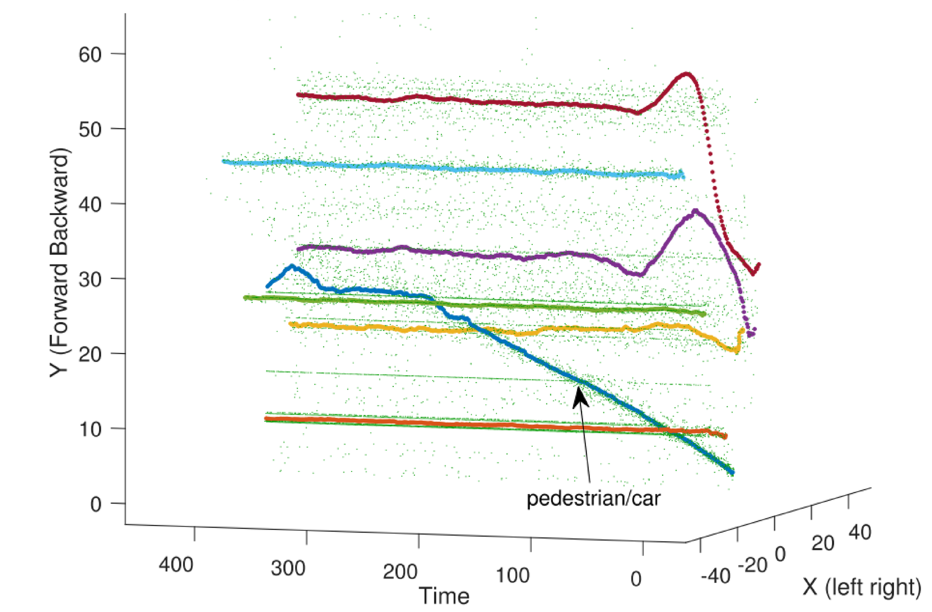

Fig 7(c): DBSCAN initialization with RFCM for actual field data

Conclusions

- The proposed RFCM method is able to outperform the conventional FCM method in improving data association performance, which leads to improved tracking performance using the EKF
- Simulation results using simulated and field data have proven the efficacy of the proposed method

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