Manifold Learning Algorithms for Sensor Fusion of Image and Radio-Frequency Data

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Abstract—**This paper presents a joint manifold learning based heterogenous data fusion approach for image and radio frequency (RF) data. A typic scenario includes several objects (with RF emitters), which are observed by Medium Wavelength Infrared (MWIR) cameras and RF Doppler sensors. The sensor modalities of images and Doppler effects are analyzed in a way that joint manifolds can be formed by stacking up the image and Doppler data. The image data provide the aerial position and velocities of objects while the Doppler data represent the radial speeds of the objects. The proposed fusion approach exploits the manifold learning algorithms for fast and accurate sensor fusion solutions. The fusion framework has two phases: training and testing. In the training phase, the various manifold learning algorithms are applied to extract the intrinsic information via dimension reduction. Then, the raw manifold learning results (i.e., the dimension reduction results) are mapped to object trajectories of interest. The fusion results are compared with the ground truth data to evaluate the performance, based on which optimal manifold learning algorithm is selected. After the training phase, the manifold learning matrices and linear regression matrices are fixed. These matrices are used in the testing phase for multiple sensor data applications. Eight manifold learning algorithms are implemented and evaluated on Digital Imaging and Remote Sensing Image Generation (DIRSIG) scenes with MWIR data as well as distributed radio-frequency (RF) Doppler data from the same scene.**

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1. INTRODUCTION

In many site-monitoring scenarios using multi-sensor modalities, the data streams not only have a high dimensionality, but also belong to different phenomena. For example, a moving vehicle may have an emitter that transmits radio-frequency (RF) signals, its exhaust system sends acoustic signals, and its perspective observed which may be collected by passive RF sensors, acoustic sensors, and video cameras; respectively. These cases demonstrate that a moving object is observed by three different modalities (data streams collected by passive RF sensors, acoustic sensors, and cameras) could benefit from sensor fusion to increase the tracking accuracy.

Sensor fusion includes low-level information fusion (LLIF) in which raw data is processed upstream near the sensors [1] for object and situation assessments such as extraction of color features from pixel imagery [2][3][4]. High-Level Information Fusion (HLIF) [5] includes the downstream methods in which context is used for sensor, user, and mission refinement. Machine analytics exploitation of sensor data [6] and game theoretic approaches [7][8][9] can support operational relevant scenarios in which users don't have the time to examine all the data feeds and perform real-time sensor management and decision analysis.

Sensor fusion is typically performed by combining the outputs (decisions) of several signature modalities through decision-level fusion [10][11]. While this data fusion approach improves the performance by incorporating decisions from different modalities, it requires the consideration of the correlation/dependence between data of different modalities. All the data in the measurement domain factually reflects the same objects of interest, which indicates that the measurements of different modalities have strong mutual information between them. The transformation from

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sensor data to a decision introduces information loss [11] , while feature information such as track pose [12] retains salient information. How to efficiently fuse all the data of different modalities in the measurement domain with a tolerable cost is investigated in this paper through *feature-level fusion* using a joint manifold learning (JML) approach [13].

This paper presents a JML based heterogeneous data fusion approach for image and radio frequency (RF) data. A typical scenario includes several objects (with RF emitters), which are observed by Medium Wavelength Infrared (MWIR) cameras and RF Doppler sensors. The objective is to detect and track an object by exploiting its total signature content (e.g. IR and RF signatures). The sensor modalities of images and Doppler effects are analyzed in a way that joint manifolds can be formed by stacking up the image and Doppler data. The image data provide the position and velocities of objects while the Doppler data represent the radial speeds of the objects. The proposed fusion approach exploits the manifold learning algorithms for fast and accurate sensor fusion solutions.

The fusion framework has two phases: training and testing. In the training phase, the various manifold learning algorithms are applied to extract the intrinsic information via dimension reduction. Then, the raw manifold learning results (i.e., the dimension reduction results) are mapped to object trajectories of interest. The fusion results are compared with the ground truth data to evaluate the performance, based on which optimal manifold learning algorithm is selected. After the training phase, the manifold learning matrices and linear regression matrices are fixed. These matrices are used in the testing phase for multiple sensor data applications.

Eight manifold learning algorithms are implemented and evaluated on Digital Imaging and Remote Sensing Image Generation (DIRSIG) scenes [14] with MWIR data augmented with distributed radio-frequency (RF) Doppler data. The fusion performances are evaluated for several scenarios: one vehicle with all sensor data, one vehicle with occlusion in some image data frames, two vehicles with all sensor data, and two vehicles with occlusion in some image data frames. These numerical results show that the proposed heterogeneous data fusion approach can discover the embedded low intrinsic dimensionalities from the high dimensional sensor data. Promising results are obtained to demonstrate the effectiveness of the manifold learning algorithms in sensor fusion.

The rest of the paper is organized as follows. Section 2 reviews the manifold learning algorithms for dimensionality reduction (DR). Section 3 introduces a joint manifold learning fusion (JMLF) framework. Section 4 presents and analyzes the numerical results of the framework applied on DIRSIG datasets. Conclusions and future work are covered in Section 5.

2. MANIFOLD LEARNING ALGORITHMS FOR DR

Manifold learning [15] is an approach to non-linear dimensionality reduction. Algorithms for this task are based on the idea that the dimensionality of many data sets is only artificially high. Figure 1 gives an example of 2-D manifolds embedded in a 3-D space. The right is a 3D Swiss roll. The associated 2D manifold is shown left.

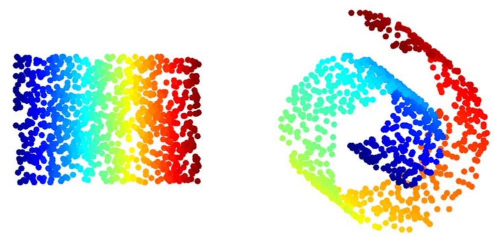

Figure 1. A 2-D manifold embedded in a 3-D space

Figure 2 demonstrates the application of manifold learning algorithms in dimensional reduction of 3D Swiss Roll, which has a 2D embedded manifold (Figure 1).

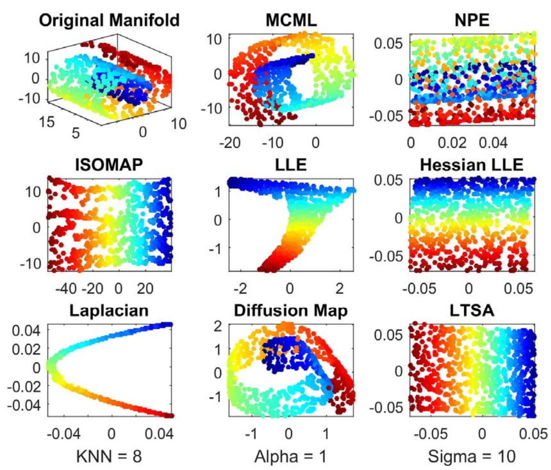

Figure 2. Dimensionality reduction of 3D Swiss roll based on nonlinear manifold learning algorithms

These MATLAB plots provide the comparison of eight manifold learning algorithms. The maximally collapsing metric learning (MCML) [16] provides a method to learn low dimensional projections of the input data. The neighborhood preserving embedding (NPE) [17] is a dimensionality reeducation algorithm with the focus on preserving the local manifold structure. ISOMAP [18] is one of several widely used low-dimensional embedding methods. It is used for computing a quasi-isometric, low-dimensional embedding of a set of high-dimensional data points. Locally linear embedding (LLE) [19] seeks a lower-dimensional projection of the data which preserves distances within local neighborhoods. Hessian LLE [20] is a method of solving the regularization problem of LLE. It revolves around a hessian-based quadratic form at each neighborhood which is used to recover the locally linear structure. Laplacian Eigenmaps [21] uses spectral techniques to perform dimensionality reduction. Diffusion maps [22] leverage the relationship between heat diffusion and a random walk to perform DR or feature extraction. Local tangent space alignment (LTSA) [23] seeks to characterize the local geometry at each neighborhood via its tangent space, and performs a global optimization to align these local tangent spaces to learn the embedding. For the Swiss roll DR problem, Hessian LLE and LTSA obtained better results than others.

3. JML Based Sensor Fusion Framework

Joint Manifolds for Heterogenous Sensor Data

For the heterogenous multiple-sensor data-fusion problem, each sensor modality (k) forms a manifold, which can be defined as:

$$\mathcal{M}_k = \{p_k = f_k(\theta) : \theta \in \Theta\} \tag{1}$$

where Θ is the parameter space and p_k is a data point. A parameter θ is the intrinsic variable or variable set in observed phenomena $f_k(\theta)$, which changes as a continuous function of the parameter θ.

For a total of K sensors, there are K manifolds. A product manifold can be defined as

$$\boldsymbol{\mathcal{M}} = \mathcal{M}_1 \times \mathcal{M}_2 \times \dots \times \mathcal{M}_K \tag{2}$$

Then a K-tuple point is

$$\boldsymbol{p} = p_1 \times p_2 \times \dots \times p_K \tag{3}$$

Accordingly, a joint manifold is defined as

$$\boldsymbol{\mathcal{M}}^* = \{\boldsymbol{p} \in \boldsymbol{\mathcal{M}} : p_j = \psi_j(p_1), j \in [2,3,\dots,K]\} \tag{4}$$

The definition requires a base manifold denoted by eq. (1), to which all other manifolds can be constructed using mapping ψ_k. The base manifold can be any manifold. Without loss of generality (WLOG), the first manifold is set as the base manifold.

A joint manifold example is shown in Fig. 3. The base manifold is an angle $\theta \in [-\pi/4,\ 7\pi/4)$. The second manifold (x, y) position of a point moving along a circle with a fixed radius of one meter and angle specified by θ. Then, the joint manifold is a helix $(\theta, \cos\theta, \sin\theta)$.

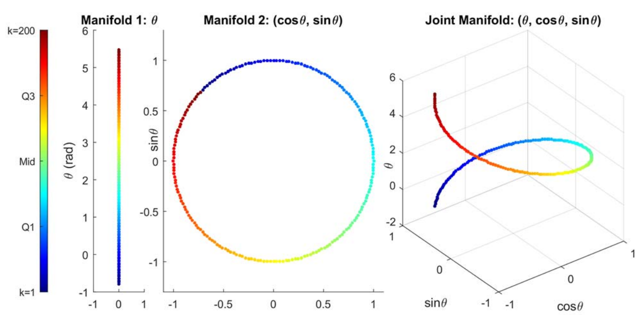

Figure 3. Reprint of the sample helix joint manifold [13]

It is shown in [13] that joint manifold structure can lead to improved performance for dimensionality reduction and manifold learning. In other words, the joint manifold structure can help us to find the intrinsic variables from high dimensional data.

In the DIRSIG datasets [14] (as shown in Figure 4), there are two types of heterogeneous data sources: video measurements based on a medium wave infrared (MWIR) sensor, and three distributed radio-frequency (RF) sensors. The MWIR sensor is in the center of the view of interest, and three distributed RF sensors are placed at Center, North, and West, respectively. The center location is co-located with a video camera with a nadir perspective. The camera records the vehicle movements within field of view (FOV) and the distributed RF sensors will receive the signals strength (e.g., RSSI) from the emitter/emitters presumably located in one or more of the moving vehicles (depending on the simulated scenario chosen).

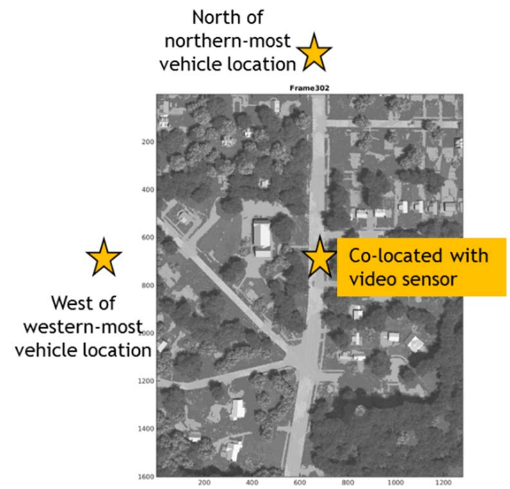

Figure 4. Heterogenous Sensors in a DIRSIG dataset

After preprocessing the MWIR image sequences or videos, a pixel location of each moving object is obtained. Since the MWIR sensor is stationary, we applied the background subtraction to quickly process the data from the camera.

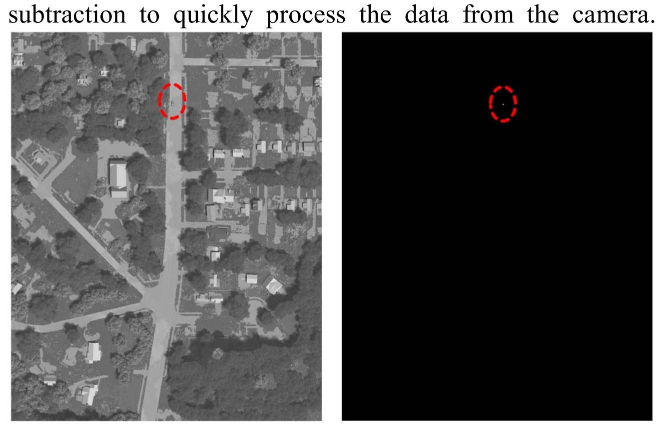

Figure **5** shows an example of MWIR data and the associated background subtraction results. Based on the pixel locations and the ground sample distance (GSD), the real-world locations of moving vehicles are estimated, in this case one vehicle moving from North to South indicated by the red circle.

Figure 5. An example of MWIR data preprocessing

Doppler shifts are obtained from the received RF samples. Then, the radial speed is calculated based on the following Doppler shift equation (where f_c is the transmitted frequency 1.7478 GHz by a vehicle, c is the light speed, v is the relative velocity (radial speed) of object and sensor, and v is considered negative when the source is approaching):

$$\Delta f = f_c\sqrt{\frac{1-\frac{v}{c}}{1+\frac{v}{2}}} - f_c \approx -\frac{v}{c} f_c \quad \left(given\ v \ll c\right)$$

$$= -\frac{17.478 \times 10^8}{2.99792458 \times 10^8} v = -5.83v \qquad (5)$$

For the DIRSIG dataset, J = 4, which includes one MWIR and three distributed RF sensors. The intrinsic parameters θ are the object's 3D location (x, y, z) and the velocities. Per the definition of joint manifold, the sensor data cannot form a joint manifold because the z dimension cannot be observed by MWIR sensor (the base manifold). However, a joint manifold can be formed if the intrinsic parameters are set to $\theta = (x, y, \dot{x}, \dot{y})$. This approximation is valid since the vehicles are moving on the ground and the heights, z, of vehicles are almost fixed ($z = 114m$ and $\dot{z} = 0$ in our DIRSIG datasets).

Therefore, all sensor measurements can be stacked to form a seven-dimensional (7D) vector for each vehicle, including one 4D MWIR data and one 1D RF sensor data from each of the three RF sensors. On the joint manifold, manifold learning algorithms are employed to reduce the high dimension sensor data to the low dimensional intrinsic parameters, which are related to the detected object positions and velocities.

A Joint Manifold Learning Framework (JMLF)

Figure 6 shows the block diagram of the proposed JMLF framework. The joint manifolds (7D) are formed by stacking up all sensor data. Then in the learning or training stage, the ground truth data is used to train the JMLF framework by evaluating and selecting manifold learning algorithms. Since the goal is to determine object tracks, the raw manifold learning results (i.e., the dimension reduction results) are mapped to object trajectories via linear regression. The reason for selecting the linear regression mapping is justified as follows. The intrinsic low dimensional data (4D for each vehicle), extracted by manifold learning algorithms from high dimensional data, are the linear transformation (i.e., rotation and shift) of vehicle positions and velocities. The nonlinearities of the sensor data (Doppler data in DIRSIG datasets) are handled by manifold learning algorithms.

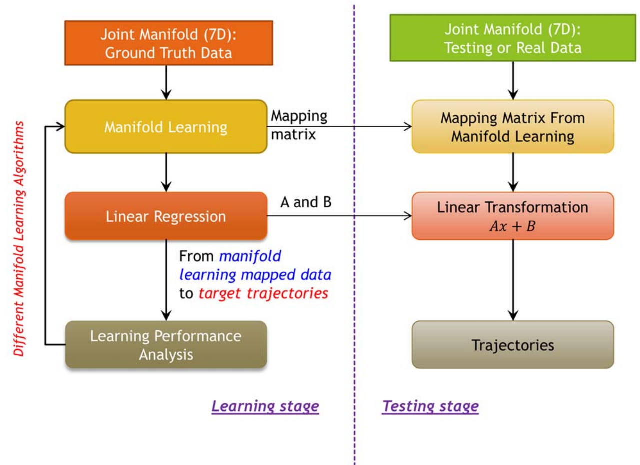

Figure 6. A JMLF for heterogeneous data fusion

The learning performance is first evaluated by the similarity between the raw manifold learning results and the ground truth data. Then the position and velocity errors between the linear regress and training data are exploited to further distinguish the best manifold learning algorithms from the winners of the first round.

After the learning stage, the manifold learning matrix and linear regression matrices are fixed. These matrices are used in the testing stage for testing data and real sensor data in the DIRSIG datasets. The sensor data follow a similar path from raw upstream data to joint manifolds, manifold learning algorithms, linear transformation, and then to object trajectories. The whole process is fast because there are only simple mathematic operations of matrix multiplication and addition.

4. Numerical Results and Analysis

Scenario

For the DIRSIG dataset we picked, there is one vehicle traveling from North to South. The ground truth (for the training purpose) is shown in Figure 7. The object emits a single tone (a sinusoid signal) at the carrier frequency of 1.7478 GHz. There are three Doppler sensors denoted by red markers in the plot. One MWIR video sensor is collocated with a nadir Doppler sensor in the center of the scenario, which has a total of 599 frames or snapshots. One snapshot has a duration of 1/20 s. The received RF signals are sampled at a rate of 1.575×10^8 samples per second, with 7.875×10^6 samples per snapshot. The Doppler shifts and radial speeds are shown in Figure 8.

Training

Based on the raw results, as shown in Figure 9, of eight manifold learning algorithms, we picked MCML and NPE in the first round, because their raw results match the original base manifold. Please note that the base manifold has 4 dimensions (positons and velocities) and we only display the position information for the illustration purpose (2D information is easy to visualize and compare).

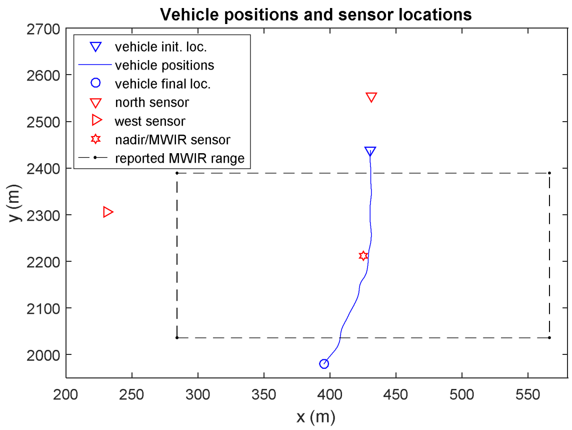

Figure 7. A scenario with ground truth data

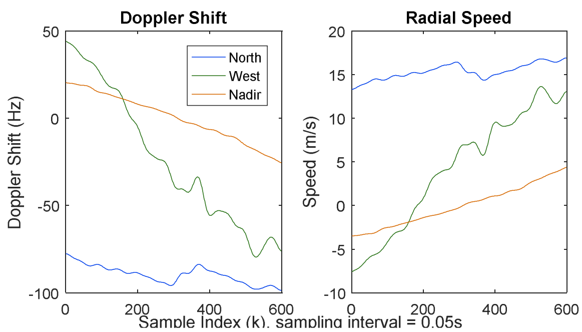

Figure 8. Ground truth data for doppler sensors

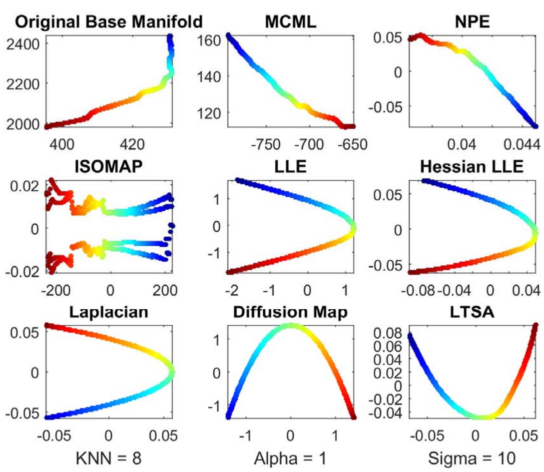

Figure 9. Raw results from manifold learning algorithms

In the second round, we compare MCML and NPE. The MCML training results and performance is shown in Figure 10 and Figure 11, respectively.

Similar, we show the training results and performance of NPE in Figure 13 and Figure 12, respectively. From these results, we determined that NPE is better than MCML for the scenario because it has smaller position errors and similar velocity mismatches.

In the next subsection, we apply the trained JMLF-NPE to various testing data as well as sensor data in the DIRSIG dataset.

Testing

We tested the JMLF-NPE on three setups: *i*) we added white noises to the training data; *ii*) we added the shifts (5 meters in *x*-axis, and 3 meters in *y*-axis) on the data in *i*); *iii*) we processed the real sensor data in the DIRSIG data. The results and performance of case-*i* is shown in Figure 14 and Figure 15.

Figure 16 and Figure 17 are the results for case-*ii.* The JMLF works well in case-*ii*, where the testing data are in the training data. The NPE algorithm learned an internal model of the data, which can be used to map points unavailable at training time into the embedding in a process. It is often called out-of-sample extension (Figure 18).

The third case we studied is the real sensor data in the DIRSIG dataset. The prepressing results are shown in Figure 19. As shown in Figure 7, there is no MWIR data for first 75 frames and last 78 frames. We got good testing results in Figure 20.

5. Conclusions

In this paper, we developed a JMLF for heterogeneous data fusion. The heterogeneous sensor data were stacked-up as the inputs to the JMLF to form a joint sensor-data manifold. Eight manifold learning methods were applied to discover the embedded low intrinsic dimensionalities from the high dimensional sensor data. Training data were used to tune the JMLF mapping from the intrinsic dimensionalities to the multi-modality object tracking results.

Acknowledgements

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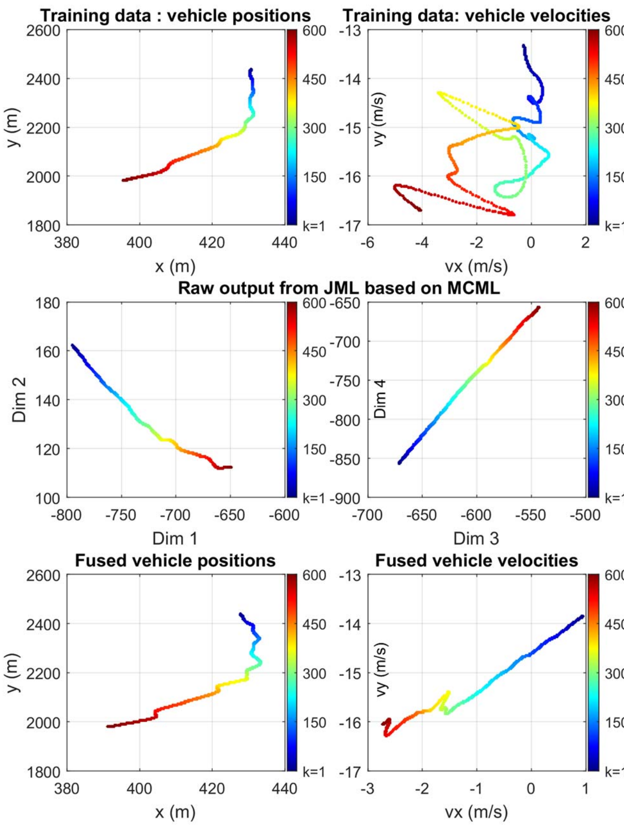

Figure 10. Training results of MCML

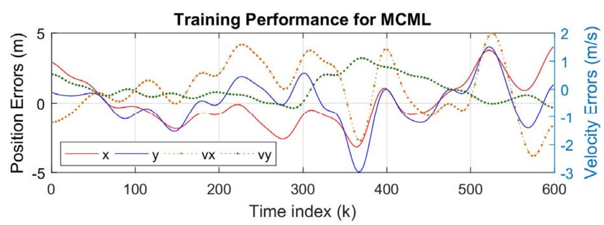

Figure 11. Training performance of MCML

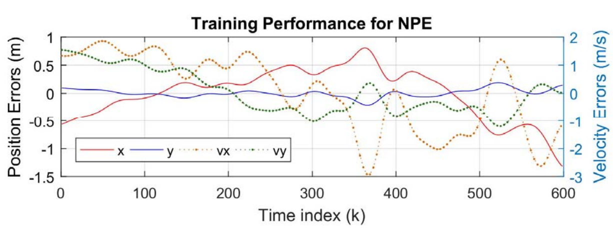

Figure 12. Training performance of NPE

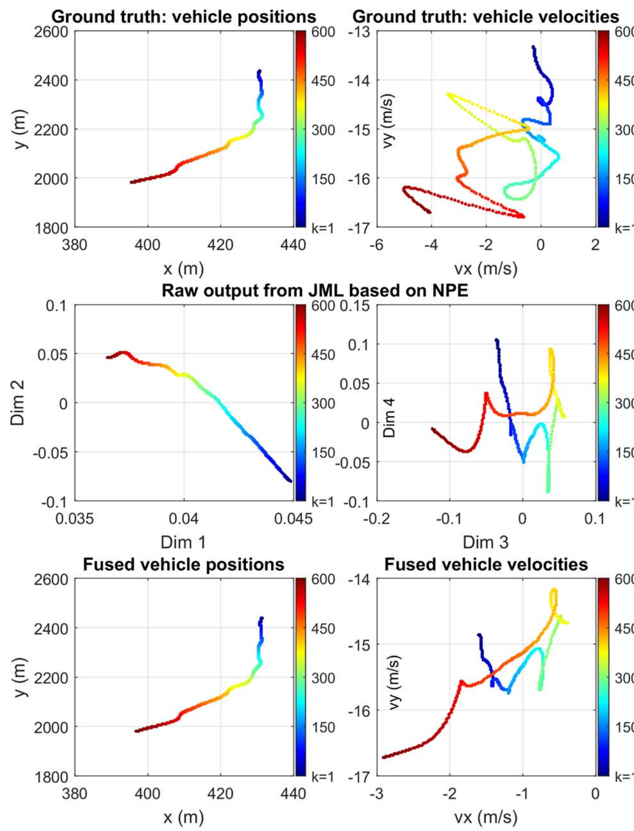

Figure 13. Training results of NPE

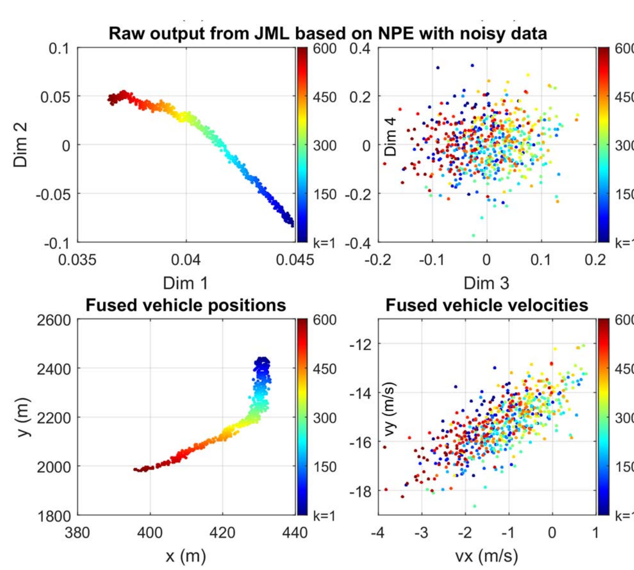

Figure 14. Testing results for case-*i*

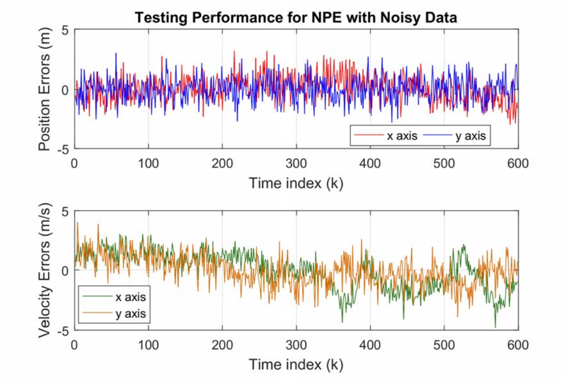

Figure 15. Testing performance for case-*i*

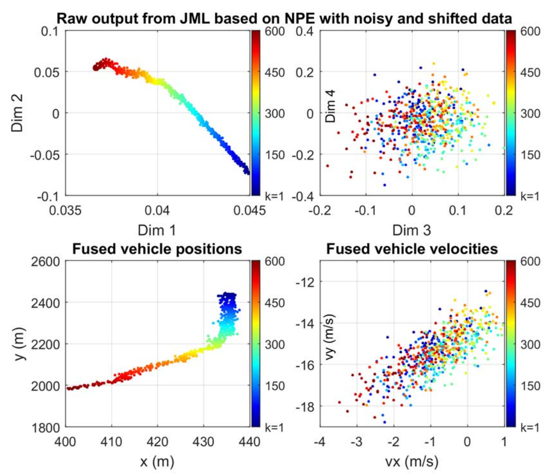

Figure 16. Testing results for case-*ii*

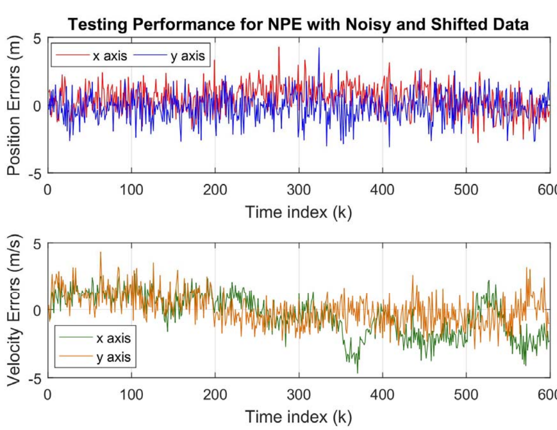

Figure 17. Testing performance for case-*ii*

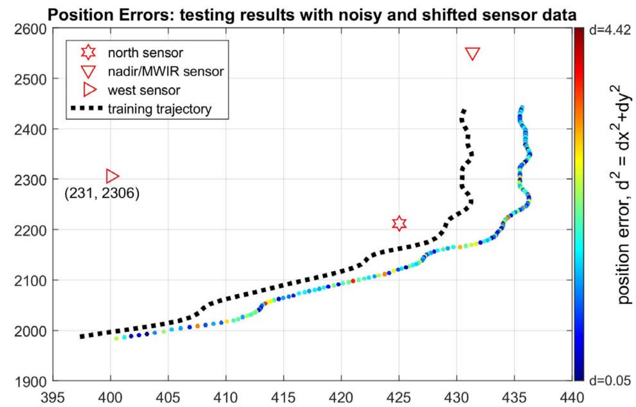

Figure 18. Out-of-sample extension in case-*ii*

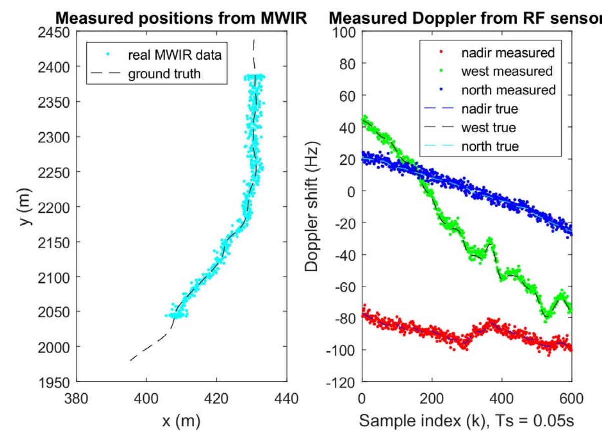

Figure 19. Prepressing results for case-*iii*

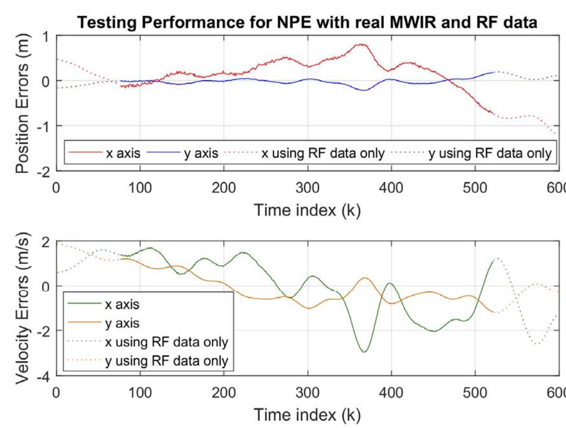

Figure 20. Testing performance for case-*iii*

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BIOGRAPHIES

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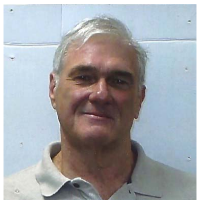
Peter Zulch *received his Bachelors, Masters, and Doctorate from Clarkson University in 1988, 1991, 1994 respectively. From 1994 to the present he has been employed by the Air Force Research Laboratory (AFRL). From 1994 to 2007 he worked for the AFRL Sensors Directorate where his interests included multidimensional adaptive signal processing with applications to Airborne Early Warning RADAR, space based radar, waveform diversity, multi-static radar, and active noise control. From 2007 to the present Dr. Zulch is employed by the AFRL Information Directorate applying the previous interests to signal intelligence pursuits such as geo-location and upstream data fusion. Dr. Zulch is a senior member of the IEEE.*



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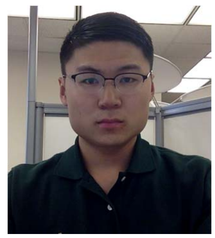

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