THE ANDREW & ERNA VITERBI FACULTY OF ELECTRICAL ENGINEERING

SIPL Signal and Image Processing Lab

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Radar Target Classification Using Micro-Doppler Signature and Diffusion Map

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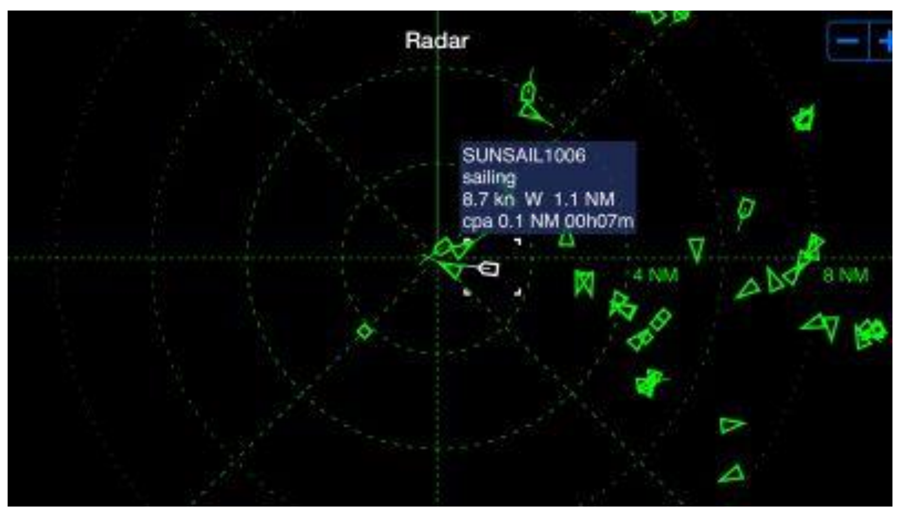
In collaboration with RADA™

Introduction

- Due to the increasing usage of unmanned aerial vehicles (UAVs) for military missions including intelligence and armed attacks, a way of detecting UAVs is essential.
- Traditionally this was achieved by RADAR systems, however birds could cause a false alarm since they have similar velocities and radar cross section (RCS)..
- Micro-Movements of the target, such as rotating propellors, cause scattering of the RADAR signal with different frequency shifts – called Micro-Doppler.
- This effect can assist us in distinguishing between UAVs and other objects.



RADAR system

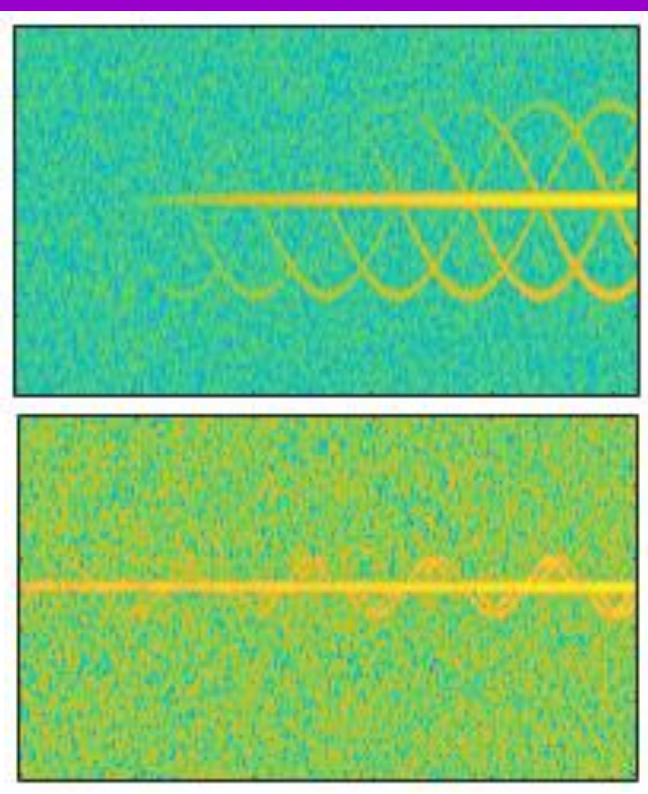
Goals

- Develop an algorithm to distinguish between UAVs and birds.
  - Use the Range-Doppler map as an input.
  - Robust algorithm for different configurations of the RADAR system.
  - Low classification time.

Challenges

- Low amount of training data.
- Inconsistent data structure.
- The diffusion map algorithm *can't* be split into train and test set.

Simulation

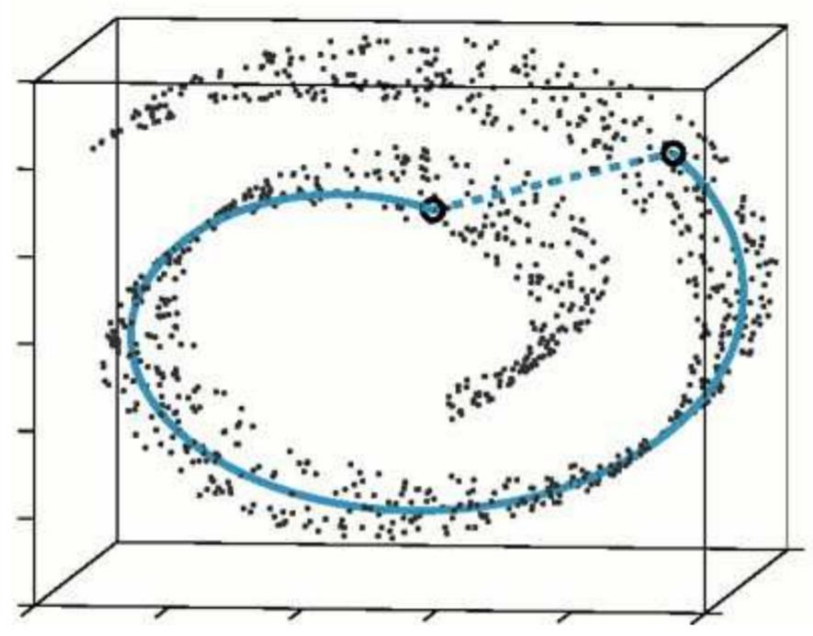


RADAR signal simulation
Of a UAV (above) and a bird (below)

- A MATLAB simulation was created as a tool for a testing and evaluating classic and advanced algorithms
- This allows us to create many samples with controlled parameters (SNR, RCS, etc.)

Manifold Learning

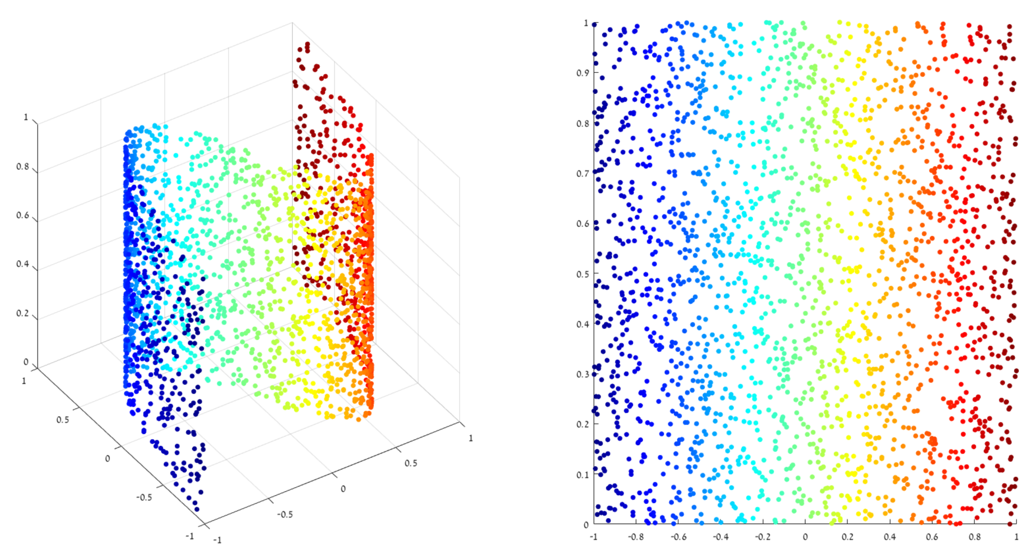
- In its full, high dimension space, the data can be represented as a lower dimension subset.
- This dimensionality reduction is not necessarily linear.
- The Euclidean distance ignores this property while calculating the distance between 2 points.
- It is therefore expected that a learning method that takes the structure of the data into consideration will have a higher success rate.



Example of the Swiss Roll, where the two highlighted point have a small Euclidean distance (dashed line), but a large distance on the surface that represents the data (solid line)

Diffusion Map

- Assume that for nearby points, the Euclidean distance approximates that surface distance well.
- Construct a stochastic matrix P such that each element describes the proximity of each pair of points.
- P can be considered as a transition matrix of a Markov chain.
- Repeatedly applying the transition matrix will make the points diffuse over short distances and will give a good indication of the surface distance between each pair of points. This is called 'Diffusion Distance'.

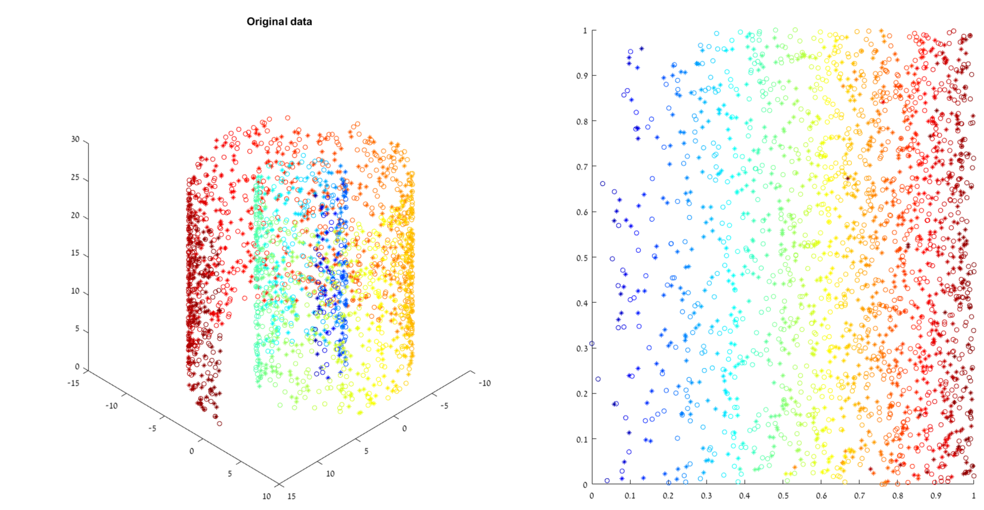


Example data (left) and it's non-linear embedding (right)

- By calculating and transforming the Eigenvectors and Eigenvalues of P, each data point can be embedded in a new space.
- The Euclidean distance in the embedded space *is equivalent* to the diffusion distance in the Euclidean space.
- Some dimensions of the embedded space can be discarded with minimal loss for dimensionality reduction

Out of Sample Extension

- The diffusion map algorithm can't be used to embed new points.
- This means that the *entire* algorithm must be repeated *for each* new sample.
- Out of Sample Extension solves this by approximating the embedding function.
- Each point is represented as a linear combination of every other embedded point, with a weight proportional to the distance.
- This representation is not exact, and there is an error between the two values.
- This process is repeated, with finer detail, until the error is sufficiently small.
- Using the results from this process, an approximation of the embedding of new data points is calculated similarly.
- This is called Laplacian Pyramid Extension.



Embedding of points using Diffusion Map (○), and embedding of points using Laplacian Pyramid Extension (∗)

Results

- The Diffusion Map algorithm was compared to a common classical solution (PCA).
- Diffusion Map performed better for real data.
- Several pre-processing methods that were recommended in the literature were implemented, but had negligible effects.
- Some samples were always classified correctly, using a wide variety of hyper parameters, while other points were always classified incorrectly

Simulated Data		Real Data	
Classic	Diffusion	Classic	Diffusion
96.58%	92.22%	74.40%	83.12%

Results of the classical algorithm and the Diffusion Map + Laplacian Pyramid Extension algorithm

Conclusions

- Diffusion Map was successfully implemented as a non-linear dimensionality reduction step in a classification system.
- Laplacian Pyramid Extension was able to approximate the embedding of the Diffusion Map without long computation after training.
- Further investigation is required for the reason of consistent failure for specific samples.

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