# UAV Interception

#### ECE6254, Statistical Machine Learning

#### Final Project Proposal

#### Georgia Institute of Technology

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## Project Summary

In recent years the availability of small, maneuverable unmanned aerial vehicles (UAVs) has grown significantly. As a result, concern around deterring malicious intent, surveillance, and public safety has become a topic of concern. A UAV’s small size and low flight altitude means that identification methods must be capable of tracking and classifying targets in cluttered backgrounds where the object of interest may exist on a similar spatial scale to many other objects in the image. The similarity of tracking other small aerial objects such as missiles in a war zone, or birds around an airport, gives any solution to this problem even broader applicability.

This proposal intends to apply the methods of statistical machine learning to the identification and tracking of small aerial vehicles in challenging synthetic video scenes. The study will start with synthetic data, generated as a deliverable of the project, to allow increasing the image complexity as the algorithm is tested. This will give direct control over the dataset, and allow development and debugging of the tracking/classification algorithms on incrementally more cluttered environments. The importance of this proposal is to improve safety concerns regarding UAVs by providing sustained tracking to allow deterrence methods to take effect.

The plan can be broken down into four general sections. These are background generation, target model generation and animation, maximum target likelihood algorithm, and target motion tracking algorithms. Each of these can be further broken into subgroups, starting with initial research and continuing through a sequence of steps where the complexity of the problem is increased. A detailed description of the project plan is given in the following section, with an itemized list of tasks located at the end of the paper.

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| https://lh4.googleusercontent.com/RUQj-GDn8yoVL34OfvO9WzKSqS6pUEK2e9D2Tf1aQjQUy1zS95RtApBwEG8Wn1PE65RQZaz8kAGRXznhU-27Na4Q9jBg7VO-D0ryB2yHWoUYioyTa3RCCAxs_nZJv1GFXG4KT9rH  Figure 1: Ordinance UAV [Ben1] | https://lh6.googleusercontent.com/PU6MQcLt-jsMekwX7kCp0J-IHcqKj8P4qkLlfHeJy7BZfX7Niedsn9eEyONom4ETLgZ81od_7l07WWXvwxfUq6O1QP6F7kqi_s1S5fLbMnh_1D5ZRBCkDMqqd9xCVtzlp0RytlR2  Figure 2: Surveillance UAV [Ben2] |

## Detailed Description

**Background generation** will consist of an initial simple design and eventually increment to a more complex implementation. The simple design will establish synthetic images with Gaussian noise as shown in Figure 3. Generic parameters for background noise characteristics shall be adjustable by the user to simulate Low, Moderate, and High complexity benchmarks for algorithm assessment. The parameters shall include but not be limited to noise mean and variance, salt-pepper noise inclusion, and variable spatial complexity.

After the algorithm design has succeeded in tracking targets against high complexity generated backgrounds, realistic background testing will follow. This stage of testing will acquire images from an online database and perform Gaussian noise injection on the computed power spectral densities as seen in Figure 4. The noise injected shall be adjusted to generating Low, Moderate, and High complexity background for algorithm assessment.

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The goal of the background generation task is to establish a library of unique backgrounds which can be overlaid with simulated targets. Severity of the noise will strain the tracking performance and establish a realistic benchmark for real world applicability. The potential challenge revolves around selection of noise benchmarks. The expectation is that these benchmarks can be derived from estimates based on academic studies of target tracking in cluttered environments.

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| https://lh3.googleusercontent.com/1Ikr1zyragSBUudr6nZIBZFAbRyc6gKt8zEAEBVvTY4G6KiUtU00uEsOpg1VhMHKtYTMhY0x0PTenCoF5IoVvzp0rYm3TcyfgbQU5yJ1QA8FPJ9AvGuVZI5UqUgXAyg5kgSIJo41  Figure 5: Gaussian Target (Simple) | https://lh3.googleusercontent.com/OdZkljzfTZC27J2ZK1ksUfjau79JLIBnR_RM-an-OVZciQjqQYMFNTTg4TV6jG73a5mtUPcY_Aux6PyFjBA1b5SPk6ecoH_1Ajzl22zOZOv8z5vq9JLoWjag-rSKpLisWda7VRmp  Figure 6: Commercial UAV (Complex)[ Ben5] |

**Target generation** will consist of a number of sub programs, loosely divided into target model creation, target motion generation, background image integration, and post-processing. The goal is to design a set of scripts to automatically create target shapes and trajectories based on parameters input by the user. Target images and motions can then be combined with background images to build varied training and test sets.

Initial target modeling is planned to use two dimensional Gaussian blobs. The shape can then be translated to different positions in the image plane according to a time series of coordinate information, resulting in a video like progression. This progression will be saved and laid over background images or generated directly in the scene without this additional step. The former method is preferred, as it allows for code reuse with more complex models at a later stage. As time permits, this later stage will source more realistic models to replace the simple Gaussian blob. These models could be from openly available images online or 2d images generated from 3d models.

Target positions will be generated using kinetic models for ballistic motion, parameterized according to starting velocity and bearing. To model more complex motion, such as that of a drone or airplane, a stochastic model will be generated to randomly alter the trajectory of the target in a realistic manner at random points in time. In this case the physical laws dictating possible motions of a mass bearing target will be accounted for to maintain real world applicability of the results. The coordinate time series generated will also be saved and used as the true position during training and testing of the tracking algorithm.

**Maximum Likelihood Estimation (MLE)** will consist of both a simple and complex design each estimating/segmenting the target from the background. The simple MLE design will take data elements from the assumed background and target areas, acquired through windowed regions on and around the assumed target location as in Figure 7, then use these data points in selecting an optimum threshold as in Figure 8. The complex MLE design will incorporate advanced selection criteria for the windowed region to attain a more robust MLE threshold.

To apply MLE there should be sufficient data in the background area to estimate both a mean vector and covariance matrix [HyeonRef1]. Also, the distribution of the population should be approximately Gaussian [HyeonRef1]. The probability density function of the original image and the additive noise will be defined to appropriately derive the maximum likelihood and map the estimates of the background [HyeonRef2]. The same procedure will be done for the target estimation.

The benefit of the MLE method proposed it its ability to optimally select a threshold for segmenting the target and background [HyeonRef3]. This threshold is adjusted to minimize error in the target location estimation. Potential challenges include proper window sizing, background contamination of the target area, and tainted window regions increasing the threshold selection errors. These problems will be address through leveraging academic results in this domain of research.

**Target Motion Tracking** will be performed by estimating the expected target and background areas for future frames. Tracking any object can be broadly classified into three domains [Rish1]:

* **Point tracking:** Moving objects are represented by their feature points during tracking.
* **Kernel tracking:** These techniques involve computing object kernels from one frame to the next.
* **Silhouette tracking:** The aim of a silhouette-based object tracking is to find the object region in every frame by means of an object model generated by the previous frames.

This project will implement a Kalman filter to track the motion of the target. Kalman filtering is a point tracking method. Based on the Recursive Least Squares (RLS) algorithm, the Kalman filter estimates the position of an object based on previous estimates while also accounting for the dynamics of the object [Rish 2].

Two Kalman filter designs are planned. The first will estimate the position in the next frame by applying a known matrix to the data in the current frame [Rish 2]. The Kalman filter uses a 2 step predictor-corrector algorithm; first projecting the most recent state and an estimate of the error covariance forwards in time to compute an a-priori estimate of the state at the next step, then correcting the predicted state estimate by incorporating the most recent process measurement to generate an a-posteriori estimate [Rish 3].

The second design will implement the extended Kalman filter. At each point in time the object being tracked has a given range and bearing from the observer, these are generated from displacements in both the x and y directions [Rish 4]. The extended Kalman filter also implements a 2-step predictor-corrector algorithm similar to the standard Kalman design. However, due to the nonlinear nature of the process being estimated, the covariance prediction and update uses the Jacobians of the state estimate as opposed to original the state estimates as-is [Rish 5].

## Project Tasks

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| Task | Leader | Deadline | Importance | Challenges |
| Generate Training and Test Data Sets | Ben/Eric | 4/02 | High | - |
| * Generated background images | Ben | 3/28 | High | Suitable Benchmarks |
| * Normalized grayscale backgrounds | Ben | 4/01 | High | N/A |
| * Gaussian blob creation script | Eric | 3/28 | High | Transfer to Complex Design |
| * Ballistic motion model | Eric | 4/02 | High | Realistic Motion Reference |
| * Stochastic motion model | Ben | 4/02 | Medium | Realistic Motion Reference |
| * Post processing script | Eric | 4/02 | Medium | Appropriate scaling |
| Target Identification Algorithm | Hyeon/Ben | 04/18 | High | - |
| * Collect Research Sources | Hyeon | 4/02 | High | N/A |
| * Disseminate Research Content | Hyeon | 4/02 | Medium | N/A |
| * Design MLE Detection Algorithm | Hyeon/Ben | 04/18 | High | Proper Window Sizes |
| * Threshold Calibration | Hyeon/Ben | 04/18 | High | Window Contamination |
| Post Detection Tracking | Rish/Eric | 04/21 | High | - |
| * Collect Research Sources | Rish | 4/02 | High | N/A |
| * Disseminate Research Content | Rish | 4/02 | Medium | N/A |
| * Simple Kalman Filter | Rish/Eric | 04/18 | Medium | Parameter Selection |
| * Extended Kalman Filter | Rish/Eric | 04/21 | Low | Parameter Selection |
| Final Project Report and Poster | Team | 05/04 | High | - |
| * Poster Creation | Rish/Hyeon | 04/25 | High | N/A |
| * Final Report | Eric/Ben | 05/04 | High | N/A |

**Challenge Descriptions**

Potential challenges in generating background images involve the selection of noise benchmarks. This challenge could be solved through academic studies which discuss background PSD qualities for Low, Medium, and High difficulty cluttered environments. A potential challenge in the Gaussian blob creation scripting relates more to the transference from the initial Simple design to the Complex design. The Complex design requires synthetic relations to UAV models which can be obtained through infrared imaging video on the public domain. Potential challenges in the Target Motion Models consist of proper modeling of UAV movement to real-life scenarios. This problem can be solved through infrared imaged video on the public domain and transferring relatable movements into our models. Potential challenges in regards to the design of the Maximum Likelihood Estimate include proper window sizing and signal/error estimate contaminations which both increase threshold selection errors. These problems will be address through leveraging academic results in this domain of research. Potential challenges in regards to the designs of the Simple Kalman Filter and the Extended Kalman Filter relate to the parameter selections. These parameters are optimally selected when correlated to the target characteristics. This challenge will be overcome by prior knowledge of the target, but genericized with the use of select heuristic algorithms.

## References

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[Rish1] <https://pdfs.semanticscholar.org/25a6/c5dff9a7019475daa81cd5a7f1f2dcdb5cf1.pdf>   
  
[Rish2] ECE 6250 Course Notes: Justin Romberg  
  
[Rish 3] <http://www.goddardconsulting.ca/kalman-filter.html>[Rish 4] <http://www.goddardconsulting.ca/simulink-extended-kalman-filter-tracking.html>

[5] <http://www.goddardconsulting.ca/extended-kalman-filter.html>