UNIVERSITY OF CALIFORNIA
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FASTPAS - FAST PREDICTIVE ARIEL SCANNING

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by

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Abstract

FASTPas - Fast Predictive Ariel Scanning

by

Sargis S Yonan

Unmanned Aerial Vehicles (UAVs) have become more prevalent in fields of work and study that benefit from having a birds eye view on a given situation. Firefighter teams have been using UAVs to find the origin of fires, and where fires are spreading to. Scientific researchers have been using aerial thermal imaging to determine rates of change in ice growth and melting, and thermal exchange between the ocean and atmosphere.

The use of autonomous UAVs could benefit rescue teams, firefighters, scientific researchers, and private sector industries in the interest of time and data discovery. Using a single or multiple UAVs in a flying network, an area with fields of interest can be scanned efficiently completely autonomously. By simply drawing on a map the general area wished to be scanned by the autonomous fleet, a deployed pod of these UAVs can stream back, to a ground station, live aerial information. This mapping time can be greatly reduced with the use of statistical interpolation techniques that help the pod or single UAV avoid having to scan an entire region, but rather, have the UAVs scan the areas with the lowest level of confidence in prediction.

The Kriging Method, a popular interpolation tool offers a prediction and a variance of prediction, but is computationally expensive because of constant fitting procedures. We can exploit the Kriging variances generated by our prediction to motivate the UAVs to

autonomously steer in the areas of least confidence until a minimum confidence in prediction is achieved for an entire unknown field. By designing a computational efficient algorithm based on a Universal Kriging Method, the system is feasible and could benefit a large group of potential users.

To all those who think flying robots are cool, and to my mother, Marina.

Acknowledgments

I want to thank Sharon Rabinovich, who helped me make sense of the various concepts involved in and out of this project. I would like to extend my thanks to the rest of the Autonomous Systems Lab at UC Santa Cruz for the support and motivation to continue this project everyday.

Part I

Mathematical Background

0.1 Variography

0.1.1 Covariance

0.1.2 Variance

0.1.3 Autocorrelation

0.1.4 Autocorrelation in A Gaussian Stochastic Process

Lag Distribution Statistics

Autocorrelation from Lag Distribution

0.2 Geospatial Autocorrelation

0.2.1 Autocorrelated Geological Stochastic Processes

0.3 Least-Squares

0.3.1 Residuals From Least-Squares

0.3.2 Fitting Continuous Functions From Discrete Data

0.4 Best Linear Unbiased Estimators

0.5 Required Graph Theory

0.5.1 Vertices and Edges

0.5.2 Path Problems

Optimizing a Route

Part II

Efficient Interpolation

Chapter 1

Introduction

There currently exists no consumer-level UAV system that can autonomously scan a perimeter of area to quickly map an unknown field. Due to the benefits of the solution to the problem, in terms of scientific research and benefit to fire fighting, I believe that designing a modified mathematical statistical interpolation method could make this system possible. Using a modified Kriging Method and a custom autonomous pod-UAV simulation, I would like to demonstrate that the system is possible, and could also benefit a variety of civil servants and scientists. We will, in this chapter, develop the tools and understanding of a method for interpolating data autonomously from just a few measured positions.

1.1 Standard Inverse Distance Weighted Sums

1.2 Kriging Prediction

It can be impossible to scan every square unit of area in a field, even with UAVs. Depending on the size of the map, it can often be most beneficial, in the interest of time flying above an area, to get a good enough prediction of the status of a field based off of a limited number of samples.

The Universal Kriging Method, also known as the WienerKolmogorov prediction, is a geo-statistical Gaussian process interpolation method historically used in fields varying from natural resource location prediction for mining to real estate value appraisals.

Using the Kriging method, the unknown prediction of interest at point s_0 is achieved via:

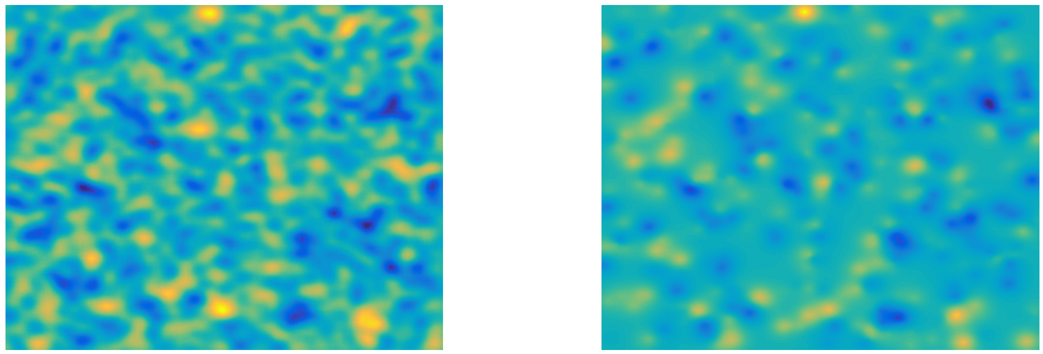
$$\widetilde{Z}(s_0) = \sum_{i=1}^{n} \lambda_i Z(s_i) \tag{1.1}$$

where λ_i is the Kriging weight associated with the sampled point at $Z(s_i)$.

The Kriging method fits values to the λ_i weights using information interpreted from the field as data comes into the system.

1.2.1 Variography in Kriging Weight Selection

The factors that play into the calculations of these weights come from the variances of disjoint points sampled in the fields as well as factors inversely proportional to the square



Randomly Generated Field   Kriging Method Predicted Field

Figure 1.1: A comparison of a random field generated using 500 random autocorrelated points, and a prediction of the field using the Kriging Method at 50 randomly sampled points. *figures generated using MATLAB.*

distances of the point in question and all other points sampled. Hence, the method also provides a variogram (a continuous approximation of variances between any given point in the prediction area and another point) with its prediction. The variogram provides what could be used as a measure of confidence in the Kriging prediction. This comes from the fact that the fields in question contain points of interest that are geospatially autocorrelated.

1.2.2 Semi-Variogram

Kriging finds a continuous variogram by computing a discrete variogram function, a *Semi-Variogram*, from points it has actually sampled

$$\hat{\gamma}(\mathbf{h}) = \frac{1}{2N(\mathbf{h})} \sum_{i=1}^{N(\mathbf{h})} \Big[Z(s_i) - Z(s_i + \mathbf{h}) \Big]^2 \tag{1.2}$$

Where $N(\mathbf{h})$ is the number of pairs of data locations that are vector $\mathbf{h}$ apart.

1.2.3 Variogram

The discrete function is then fit by a least squares to a continuous variogram that can be sampled at each point in question.

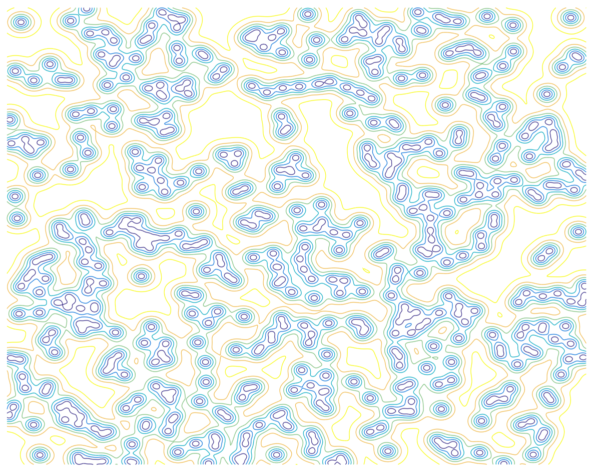


Figure 1.2: The variance of each prediction point from Figure 1. Larger spacing between the contours indicate greater variance. *figure generated using MATLAB.*

Gaussian (Normal) Kernel

Spherical Kernel

Exponential Kernel

Other Kernels

1.2.4 Choosing Kriging Weights

1.2.5 Measuring Prediction Confidence

1.2.6 Drawbacks To The Kriging Method

Although the method is optimal for data with no trends or drift, the use of the unmodified Kriging Method technique has the drawback of being computationally intensive and slow to compute in a live and timely manner. This is due to the multiple matrix inversions and least squares fittings required to calculate the weights of the interpolation from the continuous variograms. It would be desired, in the case of autonomous UAVs that must constantly steer themselves in the best direction, to quickly calculate probabilities and variances. We will further discuss methods of efficient interpolation using the Universal Kriging Method.

1.3 Natural Neighbor Selection

1.3.1 Voronoi Tessellations

Part III

Autonomous Path Finding

We know for a geospatially autocorrelated field there is a stochastic process underlying in the data we would like to predict, and therefore could interpolate further based off of the variances of two disjoint points in the field. The variances, from samples collected in the scanning process which factor into our variogram, then become our relative confidence scores of predictions in our field in question. The values in the variogram are what will be used to terminate the interpolation when a level of least-confidence in total prediction is achieved, and what will dictate the future scan locations for a UAV or a pod of UAVs.

1.3.2 Constructing a Confidence Graph

1.3.3 Confidence Optimized Path Finding

Chapter 2

Previous Work

Some other research was once performed.

Part IV

Can it fly?

Chapter 3

Introduction

3.1 Custom Simulation

3.1.1 Flying Engine

Plot Drawing

Way-point Selection

3.2 FastPAS

3.2.1 The Algorithm

3.2.2 Simulating It

3.3 Other Uses

Chapter 4

Results

Chapter 5

Conclusion

The method has proven to be a powerful interpolation method in simulations for simulated fields. The Kriging method has proven to be a working aerial mapping technique that provides a robust model for predictions and confidence scores. The goal of this thesis will be to design the algorithm for use with a pod of autonomous UAVs. A modified technique will have to first be developed to reduce the computational complexity of the algorithm by autonomously selecting optimal neighborhoods of sub-areas to run the method on.

Once the new method has been developed, an accurate simulation demonstrating its effectiveness and potential to be used in a real pod of UAVs will then be created and demonstrated. If time and resources are available, the algorithm will be ported to a real pod of UAVs to accomplish the task of autonomous scanning using thermal imaging (via infrared sensors). Tests will be conducted to prove the effectiveness and time efficiency of the newly developed algorithm.

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Appendix A

Ancillary Material

kriging formula least squares semi-v to v procedure calcuylating weights