

SAS Applications in Support
of
Off-the-shelf, Affordable, WiFi-Controlled Robots

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ABSTRACT

The application of clustering and discriminant analyses to digitized imagery can enhance multivariate strategies that incorporate in spatial information and improve classification accuracies of pixels into distinct classes. This paper reports on a SAS implemented, initial approach that investigates vector augmentation, real-time search strategies, optimal clustering, and a proposed “detection” approach to seek out and find sought-after objects across numerous digital photos. The majority of the technical details, documented in the first and second authors’ M.S. theses (Minter (2006) and Huixing (2007)), are excluded because of the required brevity of this report. Described herein as well is the quite intriguing WiFi-based, sensor-carrying platform (a 1:6 scale M5 Stewart army tank converted from RC to WiFi control by several colleagues (i.e., faculty colleagues in the Department of Mathematics and Statistics at Sam Houston State University as guided by George Mitsuoaka’s (2005) article in *ROBOT*)) for use in this initial study. It represents the initial WiFi-driven robot in this particular case; forthcoming phases are discussed as well.

1.0 INTRODUCTION

In the past decade, computer technology, digital imagery technology, and broadband capabilities have grown at an ever quickening pace, e.g., at the time of this writing, city-wide WiFi is available in more than 100 U.S. cities; the city of Houston, Texas recently contracted with Earthlink for a city-wide WiFi implementation by 2009. The state of Rhode Island has WiFi available across the entire state – moreover, on a near-term basis, WiFi is anticipated to be available on a global basis. Clearly, governments and industries are relying more and more on such technological capabilities for security reasons and for data gathering and analyses purposes. One of many ways this is being done is through the acquisition and analyses of imagery by image analysts. A problem that oftentimes exists, however, with analyzing a large magnitude of digital photos is that of having to pore over each individual image (from the multitude), in hopes of finding such things as illegal aliens crossing a border, weapons stores, various objects leading to the discovery of bodies, murder weapons, illegal objects in luggage, etc. Clustering and discriminant analyses, with pronounced improvements in computing capabilities, have improved the ability to expeditiously identify and group spatial entities to make identification a more automated and less onerous task. This paper discusses initial ways and means of using such multivariate analyses with reliance on a cost-effective platform (under \$500 in this effort) that takes advantage of existing and forthcoming prevalence of WiFi technology, to improve detection and identification of specific targets. The direct dependence on SAS up through that of the development of a GUI (Graphical User Interface) will be highlighted herein as well.

2.0 PRELIMINARIES

To obtain necessary digital imagery, an off-the-shelf, inexpensive RF controlled vehicle (the 1:6 scale M5 Stewart army tank was chosen, initially, for its payload carrying capabilities) was converted to WiFi. A forthcoming goal is to mount a digital camera (the sensor) along with a specialized web-camera (the “eye” – this later task is completed at this writing). The handheld radio frequency controller was replaced with a Linksys wireless router (the WRT54G) and an Ethernet Starter Kit to control the miniaturized mobile platform (see Appendix 2). Remote control from a laptop, via a WiFi connection (and, eventually, an onboard miniature computer, the OQO – to be mounted for added analyses), was used to control operations and for telemetering data from the vehicle while conducting real-time multivariate analyses for object detection. The planned end result of this effort (i.e., we are not there yet) is the development and initial testing of a capability that prioritizes the order and significantly reduces the number of digital images requiring further investigation by an image

analyst. The likelihood of discovery of a “highly sought-after object” is the “driver” for the image ranking methodology discussed herein. SAS is utilized as the “research software” for gaining initial insight into optimal detection directions to pursue.

The initial statistical approach discussed herein and implemented in SAS in a GUI framework (see the Appendix 3) is described in the following steps:

1. Each digital photo is converted into pixel-level digital data, composed of a series of vectors of length 3, containing each pixel’s red, green, and blue (RGB) values. This process is done using the “screen control language (SCL)” component of the Applications Frame development module in SAS as part of a GUI (graphical user interface) which increases a user’s ease when interfacing with other needed SAS modules.
2. Augmentation of each pixel vector, to include spatial information more readily; this method is a modification of the technique suggested by Cressie (1993). The end result of the use of augmentation is summarized in Section 4 below.
3. Cluster analysis is used to simplify targeted areas within a digitized image and assists in expediting the process of “detecting” a target object. Once the clusters that make up the target object are known (by referencing objects that “look” similar to the target) one can restrict the search to only those areas that are made up of the same clusters as the target itself (further expediting the process).
4. A “moving rectangular window” is employed (relying on the generalized Mahalanobis distance function in Section 3.0) to rank “target-like” objects across and within images. Based on these rankings, the time required for analyzing a larger assortment of images (which an image analyst currently has to do manually) will be reduced.
5. Summary specifics of the above approach exercised on a digital photo are discussed in the results section (Section 4.0).

3.0 TECHNICAL APPROACH/METHODOLOGY

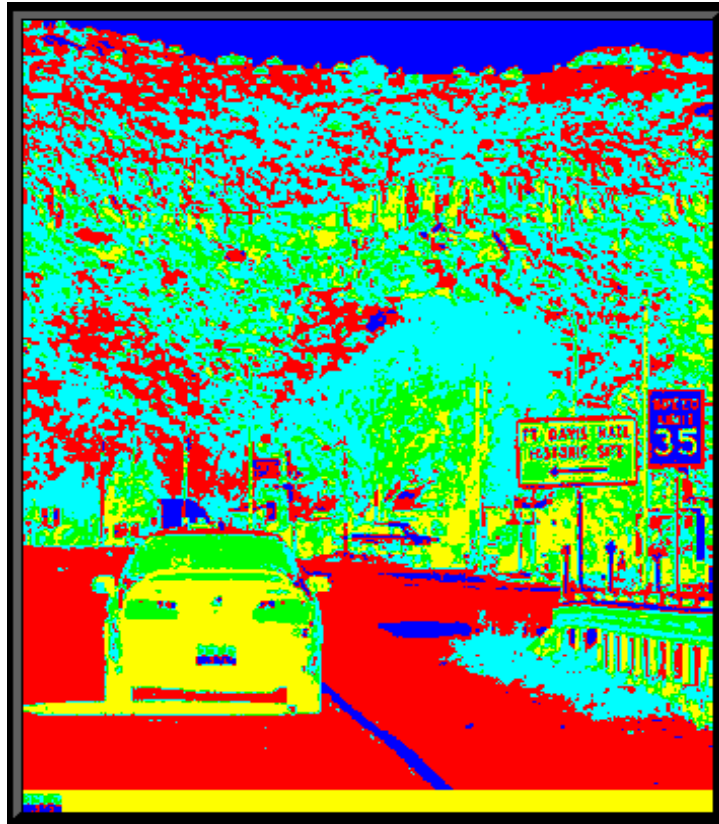
Suppose an analyst is searching for the license plate (strictly taken for example purposes here) in the following photo (taken by a 6 mega pixel camera):



A photo of the object being sought is concatenated onto the specific photo within which the search will be conducted (the photo above shows a license plate concatenated onto the photo itself – it appears in the lower left corner; the remainder of the photo is filled in (to the right) with pixels whereby all RGB values are set to 0 – which results in blacked-out pixels in the lower part of the photo).

Once the resulting image (i.e., after concatenation) is digitized and clustered, the pixels comprising the target (i.e., the license plate) in the lower left corner are assigned to clusters as well. The clustering is done by, first, determining the optimal number of clusters (using the cubic clustering criterion, the ratio of sums of squares between to within clusters, and the pseudo-F criterion). Next the optimal clustering approach is utilized (arrived at using the same criteria – again using SAS). The end result of this clustering is depicted below (after assigning false colors to the resulting clusters).

To seek the object over the digitized photo, a moving rectangular window, at least as large as the object itself, is moved throughout the digitized scene.



The specific logic resorted to is detailed further below:

1. Let $K=\{r, s, t\}$ comprise the cluster IDs of the three clusters comprising the largest proportion of the target (the optimal number of cluster IDs to utilize is awaiting further research).
2. Center the “detection window” at every occurrence of a pixel whose cluster ID is in the set K and compute the following:

$$d_{ij}^2 = (\bar{X}_0 - \bar{X}_{wij})' S_{pooled}^g (\bar{X}_0 - \bar{X}_{wij})$$

where

$\bar{X}_0$ = mean vector of RGB values for the target object restricted to only pixels from clusters with IDs from K (of course, for the object itself, this only has to be done once),

$\bar{X}_{wij}$ = mean vector of RGB values from the detection window restricted to only pixels from clusters with IDs in K.

S_{pooled}^g = the generalized inverse of the pooled variance-covariance matrix (again restricted to the same clusters as indicated above). Here the generalized inverse is utilized in case there are segments of a digitized photo that are highly discrete (i.e., for which the inverse does not exist).

3. For the the photo, assign the value

d_m^2 where:

$$d_m^2 = \min_{ij} \{d_{ij}^2\}$$

4. Rank every photo accordingly

$$d_{(1)}^2 \leq d_{(2)}^2 \leq \dots \leq d_{(m)}^2$$

The image analyst can then investigate the photos in the order of the above ascending Mahalanobis distances. Expectedly, the object will be found in the first few (e.g., the first 10 or so) rather than having to pore over the entire collection (e.g., 2000 or more --- which is currently the case in many situations where drones are used to take photos in the search of an object (e.g., a missing body) – the number of photos over a 2 mile radius oftentimes is as many as a couple thousand).

An initial SAS GUI was developed as a part of the M.S. thesis of the second author at SHSU; the specifics of this development will be discussed further at conference time. A few of the developed SAS GUI screens are included in the Appendix.

4.0 DISCUSSION AND CONCLUSIONS

From examination of the false color photos, the modified augmentation did not appear to provide a pronounced improvement for clustering (i.e., use of the original 3x1 RGB vectors appeared to be fine – the same conclusion was reinforced by a principal component analysis). This is likely due to the extreme high resolution of today’s digital cameras (unlike, e.g., improvements due to augmentation experienced historically on satellite-based, lower resolution pixel data).

The optimal clustering approach (resorted to in the above discussion) was Ward’s procedure (documented, with references, in the SAS/Statistics User’s Guide); the Expected Maximum Likelihood (EML) approach was a close competitor. The detection approach detailed in Section 3.0 will experience improvement with further modifications; currently, it appears to work fine as a “starting point”. It has two key characteristics that are desirable: 1) it is quite insensitive to the size and 2) orientation of the sought-after object. The first author completed phase 1 of this project with the development of a SAS capability to move a small rectangular window (19 by 20 in this discussion) across each photo and associate the minimum average Mahalanobis distance of the window with the pixel located at the middle position (taken to be at the (10, 10) position of the window). The smallest 380 (i.e., the number of pixels in the 19 by 20 window) pixel-level Mahalanobis distances were then highlighted and printed out as indicated in Appendix 3. Also the minimum 760 smallest pixel values were printed out as well as the window (again of size 19 by 20) whose average Mahalanobis distances were the smallest for the whole photo (see Appendix 3).

The eventual goal of this line of research is to be able to use a WiFi-controlled airborne platform (e.g., after conversion of a RC controlled helicopter, blimp or drone) to support collecting digital imagery for the purpose of detecting and identifying key “sought-after” objects based on analyses (like that discussed herein) of the collected data. The major foreseeable issues will be dictated by the size of the payload and the need for near, real-time data processing. A cost-effective, airborne

vehicle currently only allows for a small payload capability, so accommodating a 14 ounce computer and a 6 mega pixel camera will have to be dealt with eventually. As usual, SAS will be the research software utilized to carry this project to fruition.

5.0 REFERENCES

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Mitsuoka, George. "Drive a Tank BOT from your PC: Repurposed WiFi provides an elegant control solution". *ROBOT*, 1(1), Winter 2005, pp. 30-34.

Sarle, W.S. (1983), *Cubic Clustering Criterion*, SAS Technical Report A-108, Cary, NC: SAS

Appendix 1: SAS Program for a Window (of Size 19 by 20 Pixels) Search and Computation of Mahalanobis Distances for Finding the Boat (See Appendix 3)

```

data one;
set sasuser.part;
keep r g b;

proc corr data=ONE cov outp=objstats noprint;
var r g b;

DATA TWO;
SET SASUSER.img_actual;
r=red;g=green;b=blue;
IF 1<= Y<=200;
IF 1 <= X <= 250;
drop red green blue;
PROC SORT;BY X Y;

DATA COLOR;
SET TWO;
KEEP R;
FILE 'C:\HUIXING\RED.DAT';
PUT R;
FILE 'C:\HUIXING\GREEN.DAT';
PUT G;
FILE 'C:\HUIXING\BLUE.DAT';
PUT B;
DATA RED;
INFILE 'C:\HUIXING\RED.DAT';
INPUT R1-R200;
DATA GREEN;
INFILE 'C:\HUIXING\GREEN.DAT';
INPUT G1-G200;
DATA BLUE;
INFILE 'C:\HUIXING\BLUE.DAT';
INPUT B1-B200;
PROC IML;
USE RED;
READ ALL INTO R;
USE GREEN;
READ ALL INTO G;
USE BLUE;
READ ALL INTO BL;
conc=j(380,3);
stack2=j(1,6,0);
STACK=J(1,6,0);
WINOBJ=J(19,20);
use one;
read all into XOBJ;
SOBJ=J(3,3);
NR=NROW(XOBJ);NC=NCOL(XOBJ);
SOBJ=XOBJ`*(I(NR)-J(NR,NR)/NR)*XOBJ/(NR-1);
XBAROBJ=J(1,NR)*XOBJ/NR;
do b=1 to 181;
do a=1 to 230;

```

```

b19=b+18;
a20=a+19;
RSUB=R[a:a20,b:b19];
GSUB=G[a:a20,b:b19];
BSUB=BL[a:a20,b:b19];
C1= shape(RSUB,380);
C2= shape(GSUB,380);
C3=shape(BSUB,380);
CONC= C1||C2||C3;
SWIN=J(3,3);
NR=NROW(CONC);NC=NCOL(CONC);
SWIN=CONC`*(I(NR)-J(NR,NR)/NR)*CONC/(NR-1);
XBARWIN=J(1,NR)*CONC/NR;
dist = j(1,6,0);
spooled = inv(.5*(swin+sobj));
dist[1,4]=R[a+10,b+10];dist[1,5]=G[a+10,b+10];dist[1,6]=BL[a+10,b+10];
dist[1,3]=(xbarobj-xbarwin)*spooled*(xbarobj-xbarwin)`;
dist[1,2]=a;
dist[1,1]=b;
/*bet=j(930,1);
bet=stack[2:931,];
ab=1:30;
bc=1:31;

fi=((ab`)@j(31,1,1))||(j(30,1)@(bc`));
stack2=bet||fi;
create sigma from STACK2;
append from STACK2;*/

STACK=STACK//DIST;
END;
END;
/*bet=j(930,1);
bet=stack[2:931,];
ab=1:30;
bc=1:31;

fi=((ab`)@j(31,1,1))||(j(30,1)@(bc`));
stack2=bet||fi;*/
create sigma from STACK;
append from STACK;
/*proc means data=sigma;
var col3;
run;*/

data sasuser.final;
set sigma;
y=col1;x=col2;mahal=col3;
r=col4;g=col5;b=col6;
keep x y r g b mahal;
proc g3d data=sasuser.final;
plot x*y=mahal/rotate=-120 tilt=30;
run;

data sasuser.big;
set sasuser.final;
if mahal <= .5233;

```

```
proc sort data=sasuser.big;by x y;  
run;quit;
```

Appendix 2: Remote Control (RC) to WiFi Conversion Components/Configuration



Fig. 1: 1:6 Scale M5 Stewart Tank



Fig. 2: Linksys Wireless Router



Fig. 3: Ethernet Starter Kit

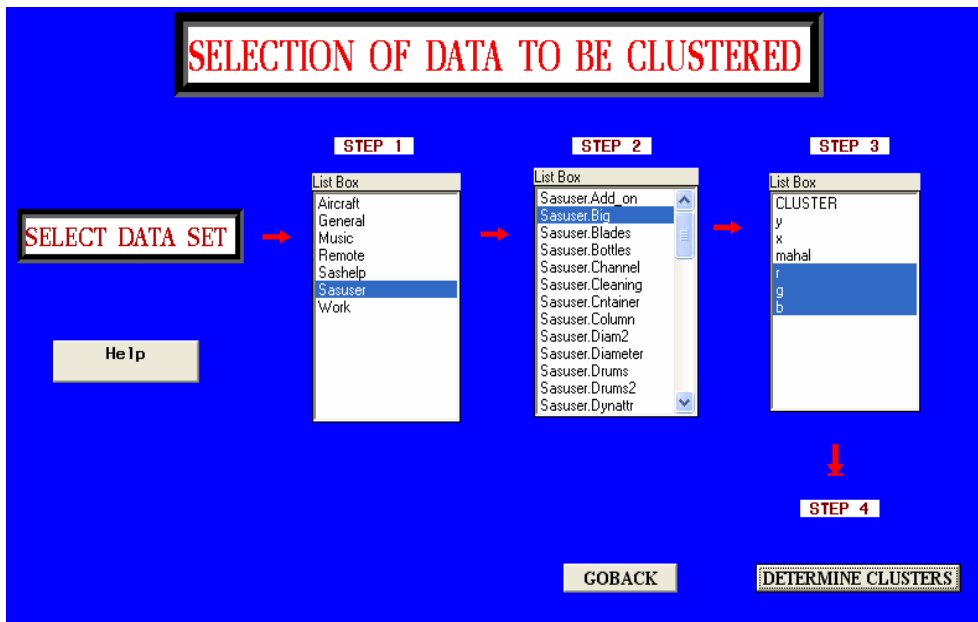


Fig. 4: Panasonic BL-C10A Webcam

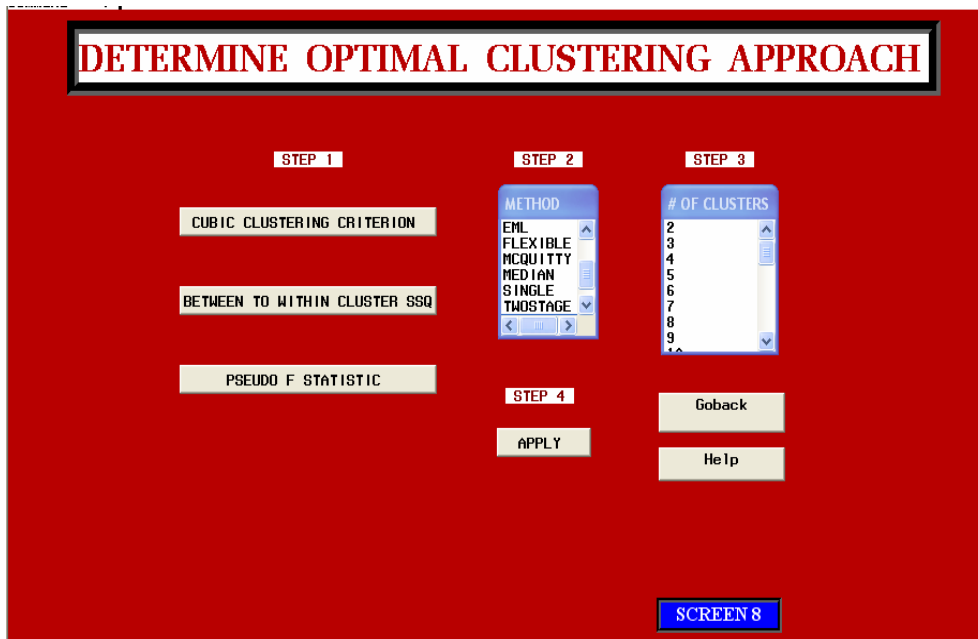


Fig. 5: Replacement of Internal RC Control Board with a WiFi-controlled Platform

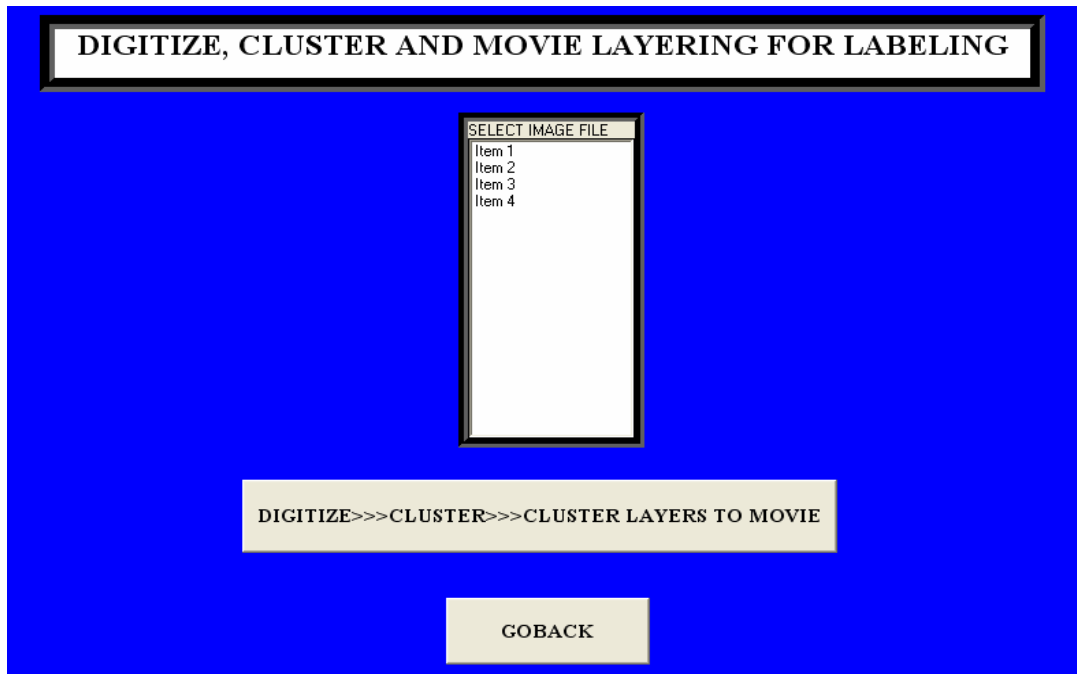
Appendix 3: Various SAS GUI Screens and Results Outputs



Screen 1: GUI Screen Utilized for Selecting the SAS Data Set to be Clustered (Also Key Screen Utilized to Exhibit Digitized Photos and Discovered Objects)



Screen 2: GUI Screen for Selecting Optimal Clusters (the Same Screen Required to Display Digitized Photos and Discovered Objects).



Screen 3: GUI Screen that Results in Digitizing All Digital Photos in a Given Folder.



Figure 1: Initial Original Picture – Object Sought: Sailboat

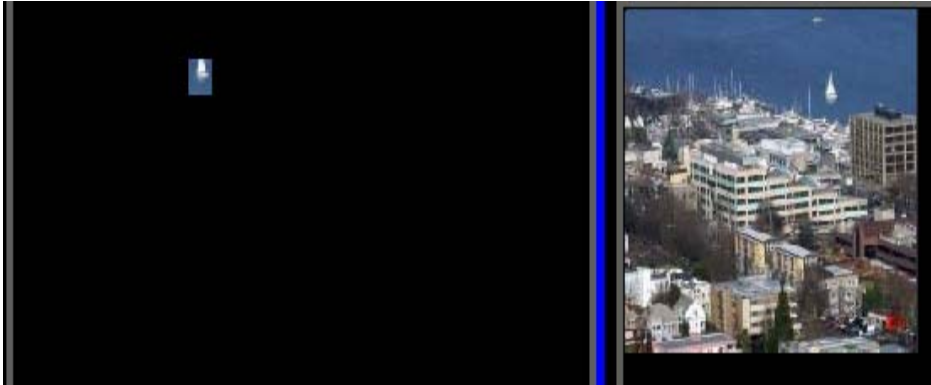


Figure 2: Display of Photo Searched (On the Right) and the Object Found the Based on the Minimum Average Mahalanobis Distance of the Smallest 380 Pixel-Level Mahalanobis Distances.

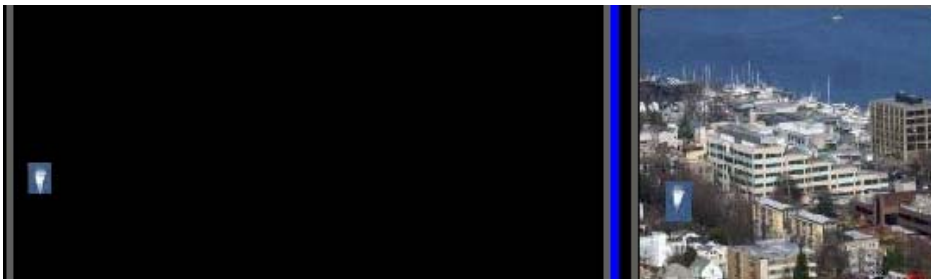


Figure 3: Rectangular Window (on the Left) with Minimum Average Mahalanobis Distances