IMPROVING INTERACTIVE CLASSIFICATION OF SATELLITE IMAGE CONTENT

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Approval of the Graduate School of Natural And Applied Sciences

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I certify that this thesis satisfies all the requirements as a thesis for the degree of Master Of Science.

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This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master Of Science.

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Abstract

IMPROVING INTERACTIVE CLASSIFICATION OF SATELLITE IMAGE CONTENT

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Interactive classification is an attractive alternative and complementary for automatic classification of satellite image content, since the subject is visual and there are not yet powerful computational features corresponding to the sought visual features. In this study, we improve our previous attempt by building a more stable software system with better capabilities for interactive classification of the content of satellite images. The system allows user to indicate a few number of image regions that contain a specific geographical object, for example, a bridge, and to retrieve similar objects on the same satellite images. Retrieval process is iterative in the sense that user guides the classification procedure by interaction and visual observation of the results. The classification procedure is based on one-class classification.

Keywords: One Class Classification, Satellite Image, SVDD, Interactive Classification

Öz

UYDU GÖRÜNTÜLERİNİN ETKİLEŞİMLİ SINIFLANDIRMASININ İYİLEŞTİRİLMESİ

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Etkileşimli sınıflandırma yöntemi, konu görsel olduğundan ve aranan görsel öz nitelikler ile ilgili hesaba dayalı etkili öz nitelikler bulunmadığından, uydu görüntü içeriğinin otomatik sınıflandırılması yönteminin ilgi çekici bir alternatifi ve tamamlayacısıdır. Bu çalışmada önceki girişimimizi uydu görüntü içeriğinin sınıflandırmasında daha yetenekli olgun bir yazılım gerçekleştirerek geliştiriyoruz. Sistem kullanıcının köprü gibi belirli bir coğrafi nesneyi içeren az sayıda görüntü bölgesi belirtmesine ve ardından aynı görüntüden benzer nesneler içeren bölgelere erişmine olanak sağlamaktadır. Erişim süreci kullanıcının sınıflandırma işlemini sonuçları görsel inceleyerek interaktif bir şekilde yönlendirdiği tekrarlamalı bir süreçtir. Sınıflandırma işlemi tek sınıf sınıflandırma yöntemine dayanmaktadır.

Anahtar Kelimeler: Tek Sınıf Sınıflandırma, Uydu Görütü İçeriği, SVDD, Etkileşimli sınıflandırma

To my family, friends and my beloved Ezgi

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I deeply thank my family for their understanding and their support.

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Chapter 1

Introduction

1.1 Problem Definition

Today, world's highest resolution commercial satellite *GeoEye-1* has a spatial resolution of $41cm$ in collecting panchromatic images and it is known that spy satellites have even better resolutions. With that much information, satellite images have many applications in agriculture, geology, forestry, regional planning, education, intelligence and warfare. However, with the increase in resolution, the amount of data to be handled accumulates. Therefore, extracting data and then exploration are becoming challenging problems in remote sensing applications. To cope with the increasing amount of data, a two phase approach, which is proposed in Oral Dalay's thesis [3] is given in Figure 1.1. The aim is to find regions of interest in first phase so as to perform more refined analysis on these regions of interest. In this study, we focus on the first phase, and one of the alternative approaches in the analysis of such large images is to profit from user interaction. For this purpose we designed an interactive classification software, which is based on active learning principles, to detect man made (structural) geographical objects. User starts with a small set of sample images, containing sought geographical object, and refines incrementally the classification performance by interaction.

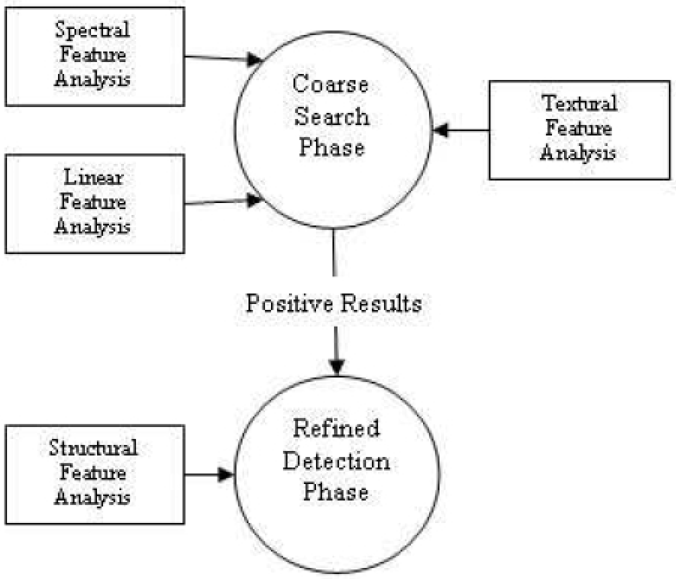


Figure 1.1: Overview of two phase classification approach.
Adapted from Oral Dalay's thesis [3]

1.2 Motivation

Classification problem, which is assignment of new objects to a class from a given set of classes based on the object features, resides at the center of many disciplines such as machine learning, data mining and pattern recognition. In a classification system, the aim is to construct decision boundaries in feature space which separate patterns belonging to different classes.

In many classification problems, particularly problems concerning visual data, unlabeled data is easy to come by but labels are expensive. For example, even in a single satellite image, the amount of the available data is very high which makes the offline training times very long. Instead, the user can help to improve the classification algorithm. In our case where classification is performed on visual data, user interaction is very convenient and meaningful. When the user comes into the scene, the framework is called active learning. In traditional supervised and unsupervised classification, data that are randomly sampled from the underlying population is usually gathered and then a classifier or a model is induced. This methodology is called passive learning. A passive learner receives a random data set from the world and then outputs a classifier or model. On the other hand, in active learning, user selects the examples hopefully in an intelligent manner in order to reduce the required labeling effort while retaining the accuracy. This framework would allow the user the flexibility to choose the data points that s/he feels which are most relevant for classification. Besides, since in our case the data is visual, the algorithm may query the user for the labels of the selected examples.

In our system, only detection of objects belonging to one class (the target class), which is sampled by the user, is required. In most cases, there will be a large imbalance between the target class and all other classes (the outliers) and it is very hard to get a complete set of examples for the outliers. For this, we use classifiers which are especially constructed for this type of problem: one-class classifiers. These classifiers aim at describing the target class and distinguish that from all other possible objects. These one-class classifiers are constructed such that they only require examples of the target class.

1.3 Achievements

We are interested in applying active learning principles for analysis of panchromatic satellite images. For this purpose, we have focused on the first phase of the interactive classification system whose overview is given in Figure 1.1. We have proposed a new approach based on one-class classifiers. Since it is necessary to prove the concept approach, a prototype has been implemented before starting the design of the final system. The overview of the proposed system is given in Figure 1.2.

The main idea behind the system is to get user feedback and iteratively improve the performance of the classifier. First step in the classification process is the generation of the initial training set of sample regions containing example target objects, by the user. Features from these regions are computed and then the result of the classification is presented to the user. From this point, user can eliminate some of the wrongly detected targets and perform classification again in an iterative manner. The two most important issues in our system are given below.

- It is an example of active learning approach.
- It is based on one-class classification problem, i.e. only examples of target class are available and an object is labeled as target or outlier.

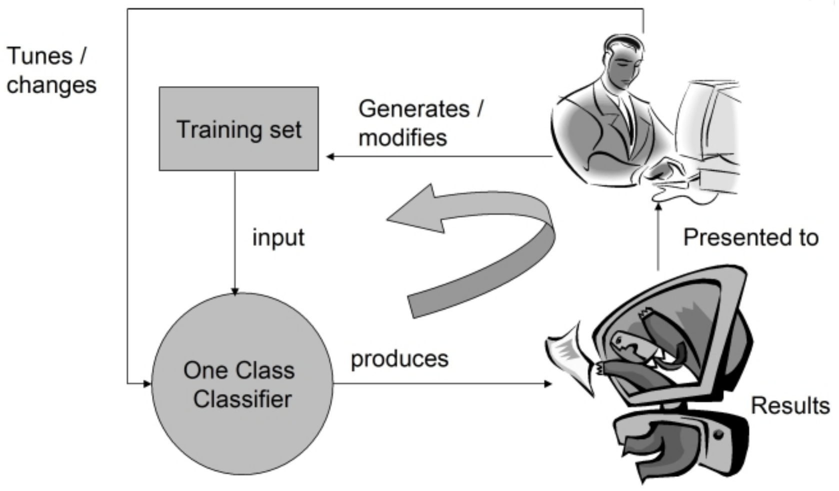


Figure 1.2: Overview of our system for finding region of interests.

1.4 Organization

The organization of this thesis is as follows. In Chapter 2 background information on techniques used in this study is given. Details of interactive classification system is described in Chapter 3. The prototype and the proposed system are evaluated in Chapter 4. The proposed system is discussed in Chapter 5, which concludes the thesis.

Chapter 2

Background Information on Classification And Feature Extraction

In this chapter, we focus on and give detailed information about methods and algorithms used throughout our study.

2.1 Feature Extraction

2.1.1 Spectral Features

In order to deal with urban areas in panchromatic satellite images, we first follow the traditional approach where mean and standard deviation of pixel gray values in the regions with fixed same size, which form the image are employed. The mean μ and standard deviation σ of pixel gray values of the regions are computed as follows.

$$\mu = \frac{1}{N} \sum_{i=1}^{N} x_i \tag{2.1}$$

$$\sigma = \sqrt[2]{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{2.2}$$

where x_i indicates gray value of pixel i and N is total number of pixels in the region.

2.1.2 Linear Features

In satellite images, man-made objects such as roads, buildings may be discriminated based on linear features. In this study, we apply the same linear feature extraction method as presented in Oral Dalay's thesis study [3]. Steps of linear feature extraction are given below.

Step 1 Canny Edge Detection: Binary edge image is computed using Canny edge detection algorithm [1] presented in Algorithm 1.

Algorithm 1 Canny Edge Detection

```
1:  Convolve Image $I$ with a Gaussian of scale $\sigma$
2:  for all pixels $p$ in $I$ do
3:    Find edge magnitude and edge direction using Sobel operator
4:  end for
5:  for each pixel $p$ with non-zero edge magnitude do
6:    inspect two adjacent pixels along the edge direction
7:    if edge magnitude of one these is greater than edge magnitude of $p$ then
8:      mark edge pixel $p$ for deletion
9:    end if
10: end for
11: Apply hysteresis thresholding with $t_{low}$ and $t_{high}$
```

Step 2 Connected Component Labeling: Boundary curves are formed by applying the connected component algorithm [9] to binary edge image. Connected component labeling algorithm is shown in Algorithm 2.

Algorithm 2 Connected Component Labelling

```
Require: binary edge Image $I$
1: for all pixels $p$ in $I$ do
2:   if $p == 1$ then
3:     if all of four neighbor pixels (top, left, top-left and top-right) $== 0$ then
4:       assign a new label to $p$
5:     else if only one neighbor $== 1$ then
6:       assign neighbor's label to $p$
7:     else
8:       assign one of the neighbors' label to $p$ and make a note of equivalences
9:     end if
10:  end if
11: end for
12: Assign a unique label for each equivalence class
13: for all pixels $p$ in $I$ do
14:   if $p$ has a label then
15:     replace its label by the label assigned to its equivalence class
16:   end if
17: end for
```

Step 3 Boundary Curve Segmentation by Polynomial Approximation: Linear segments are formed by applying the iterative end-point fit algorithm [4] given in Algorithm 3, and a non-uniform ten level histogram of the length of these line segments is computed as linear features.

Algorithm 3 Iterative End-point Fitting

```
1: Extract Edge Image with connected components computed
2: for all connected components in edge Image do
3:   repeat
4:     connect the start and end points of the connected component with a line $L$
5:     Detect edge pixel $P$ of the component with the maximum distance $d$ to $L$
6:     if $d < t$hreshold then
7:       break
8:     else
9:       Split component at $P$ into $S1$ and $S2$ and for both subsets goto 3
10:    end if
11:  until all subsets have been checked
12:  merge collinear points
13: end for
```

2.2 Classification Algorithms

Classification of a new object as target or outlier may be performed in two different ways. The first one is the classical n-class classification, while the other is one-class classification. In an n-class classification problem, a new object is assigned to one of a set of n known classes. On the other hand, in a one-class classification problem, only one class (target) is known and a new object is either assigned as target or outlier (all classes other than target).

In this study, main interest about classification is on one-class classification methods. Classical n-class classification methods are only used in final iterations of the classification process when using high dimensional features. Section 2.2.1 briefly describes one-class classification and it is mainly based on David M. Tax's thesis [15]. Section 2.2.2 briefly describes binary classification and Support Vector Machines(SVM) [17] that as used in this study.

2.2.1 One Class Classification

In one class classification method, a boundary is formed around given target objects with the aim of maximizing target acceptance rate while minimizing the acceptance of outlier objects. One-class classification methods can be analyzed in three groups:

- density estimation,
- boundary methods,
- reconstruction methods.

The most important feature of one-class classifiers is the tradeoff between false positives (outlier objects labeled by classifier a target) and false negatives (target objects labeled by classifier as outlier). This can be visualized as in Figure 2.1. The enclosed area labeled as X_T is the target distribution. The circular data description is the resulting area of a one-class classification method. The dark gray area labeled as

E_{II} is the area of false positives and light gray area labeled as E_I is the area of false negatives. As it can be observed from Figure 2.1, a tradeoff between false positives and false negatives cannot be avoided. Increasing the volume of the data description to decrease the false negatives, will automatically increase the number of the false positives. Therefore E_{II} will increase.

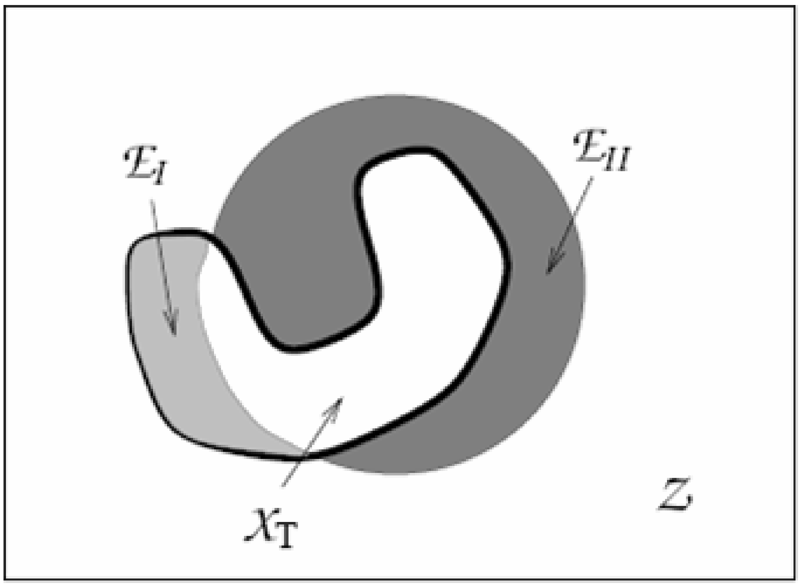


Figure 2.1: Regions in classification: a spherical data description boundary is trained around a banana shaped target distribution.
Adapted from David M. Tax's thesis [15]

2.2.1.1 Features of One-Class Classification Approaches

While comparing different one-class classification approaches, not only the errors are important, but also the following features.

Robustness to outliers: For training one class classification methods, a set which is a characteristic representation for the target distribution should be used. However, this training set may already happen to contain some outliers. A one-class classification method should reject these outliers while trying to accept the target class objects as much as possible.

Incorporation of known outliers: Available outliers in training set can be used to tighten the boundary around the target class. The model of the target set and the training procedure allow the usage of outlier objects for more precise classification. For example, when the target set is modeled with one Gaussian distribution, outlier objects cannot be used, while other methods such as Parzen [5] density estimation and support vector data description (SVDD) can use this information.

Magic parameters and ease of configuration: From the users' point of view, the number of free parameters whose values have to be determined is one of most important features of any method. These parameters are called the magic 'parameters, because they often have a big influence on the final performance and no clear rules are given how to set them. Since our system is an interactive one, a method with minimum number of magic parameters is more suitable to use.

Computation and storage requirements: A last criterion to consider is the computational requirements of the methods. This criterion is also very important, since in our system, training is performed on-line and the classification method is adaptively changed by the inputs from the user.

2.2.1.2 Density Methods

Estimating the density of the target class distribution using training data is the most straightforward method to obtain a one-class classifier. A classifier is formed by setting a threshold on this density estimation. Density estimation methods produces good results when the sample size is sufficiently high and a flexible density model is used; for example a Parzen density estimation. Unfortunately, density estimation methods require a large number of training samples to overcome the curse of dimensionality; that is the volume that should be described by classifier increases exponentially as the number of features increases [5]. Examples for density methods are:

- Gaussian,
- mixture of Gaussians,
- Parzen density estimation.

2.2.1.3 Boundary Methods

In boundary methods, a closed boundary around the target set is optimized. Even the volume is not always actively minimized, most boundary methods have a strong bias towards a solution having minimal volume. The size of the volume depends on the fit of the model to the data. In most cases, distances or weighted distances to an edited set of objects in the training set are computed. Since the distance calculation is sensitive to scaling, boundary methods, heavily relying on the distances between objects, are sensitive to the scaling of features used in classification. If we want to compare density methods with boundary methods in terms of the size of the training set required, is smaller in boundary methods. Examples for boundary methods are:

- k-centers,
- d nearest neighborhood (NN-d),
- support vector data description (SVDD).

2.2.1.4 Reconstruction Methods

In reconstruction methods, a model is fitted to the data by using prior knowledge about the data and making assumptions about the generating process. New objects can then be described in terms of a state of the generating model. We assume that a more compact representation of the target data can be obtained and that in this encoded data the noise contribution is decreased. Most of these methods make assumptions about the clustering characteristics of the data or their distribution in subspaces. A set of prototypes or subspaces is defined and a reconstruction error is minimized. Examples for reconstruction methods are:

- k-means clustering,
- self-organizing maps,
- auto-encoder networks.

The above methods differ in the definition of the prototypes or subspaces, their reconstruction error and their optimization routine.

2.2.2 Binary Classification

Binary classification is an example of n-class classification where data belongs to one of the two classes, which are available for training. In this study we use Support Vector Machines (SVM) as a binary classification method.

2.2.2.1 Support Vector Machines

Support Vector Machines are learning machines that can perform binary classification tasks. The main idea behind the SVM is that, it maps input vectors x_i to a higher dimensional space and constructs a maximal separating hyperplane. Two parallel hyperplanes are constructed on each side of the hyperplane that separates the data. The separating hyperplane is the hyperplane that maximizes the distance between the two parallel hyperplanes as shown in Figure 2.2. An assumption is made that the larger the margin or distance between these parallel hyperplanes the better the generalization error of the classifier will be.

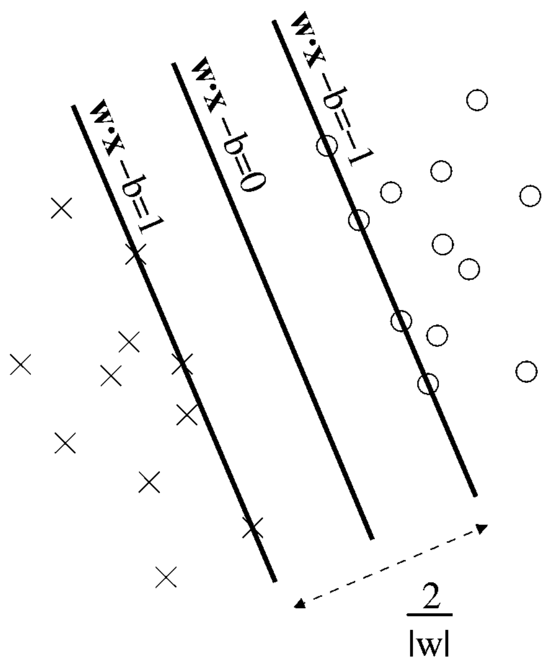


Figure 2.2: Maximum-margin hyperplanes for a SVM trained with samples from two classes. Samples along the hyperplanes are called the support vectors.

2.2.3 One-Class Classification Methods Used In This Study

In order to decide which methods to use in this study, we consider the features described in Section 2.2.1.1. In this work, we use one boundary method, SVDD and one density estimation method, Parzen, since both methods are robust to outlier objects in training data and they are able to incorporate outliers to tighten the boundary of the target class. In addition, both methods have only one free parameter which has to be set by the user and their computational power requirements can be handled by current processors adequately for an interactive system. One of the reasons for using two different methods is their performances with respect to the properties of training data. SVDD is more suitable where training data set contains a-typical samples, while Parzen density estimation produces better results with a representative training data set. Here, more information about SVDD and Parzen density estimation are given.

2.2.3.1 Support Vector Data Description (SVDD)

In SVDD method, a hypersphere is formed to contain all target objects and volume of the hypersphere is minimized to reject maximum number of outliers.

Spherical data description is defined with a center a and a radius value R and all target objects are required to be inside the sphere.

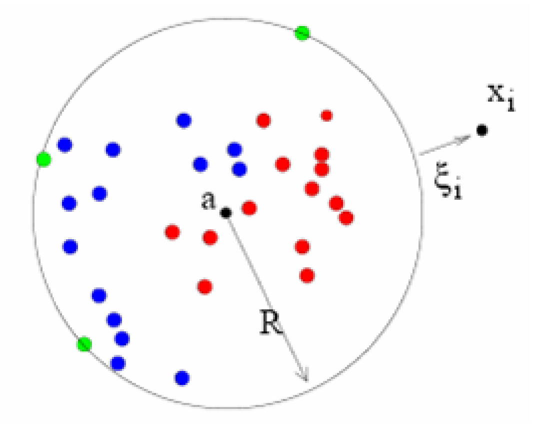


Figure 2.3: Spherical data description: hypersphere containing the target data is described by the center a and radius R. Three objects are on the boundary which are the support vectors. One object x_i is outside and has $\xi_i > 0$.
Adapted from David M. Tax's thesis [15]

Structural error is defined as $\varepsilon_{struct}(R,a) = R^2$ with the minimization of the constraint $\| x_i - a \|^2 \leq R^2, \quad \forall i$. To allow outliers in training of the classifier, it is possible for objects x_i to have a distance to the center a greater than R^2. Since those objects should be penalized, an empirical error is added to structural error with the introduction of variable $\xi, \forall x_i$. The final error is defined as $\varepsilon(R,a,\xi) = R^2 + C\sum_i \xi_i$ and the free parameters a, R, ξ should be optimized with the constraint $\| x_i - a \|^2 \leq R^2 + \xi_i, \quad \xi_i \geq 0, \forall i$. This is done by using Lagrange multipliers and final Lagrangian [14] is

$$\boldsymbol{L = \sum_i \alpha_i (x_i \cdot x_i) - \sum_{ij} \alpha_i \alpha_j (x_i \cdot x_j)} \tag{2.3}$$

where α_i is Lagrange multiplier and $x_i \cdot x_j$ is inner product between x_i and x_j.

Equation 2.3 is an instance of quadratic programming problem and several algorithms exist for the solution of this problem [10]. A new object is labeled as target when the distance to the hypersphere center is less than equal to the radius R. Spherical data description enables incorporation of outlier objects in training and it is identical to the one without outliers.

The hypersphere is a very tight model of the boundary of the data and in real life problems it does not fit the data well. To overcome this problem Kernel trick [17] can be utilized in which the data is mapped to a new representation in order to obtain a better fit between the actual data boundary and the hypersphere model. Assume we are given a mapping $\Phi(x)$ of the data which improves this fit: $x^* = \Phi(x)$. Equation 2.3 becomes

$$\boldsymbol{L = \sum_i \alpha_i \Phi(x_i) \cdot \Phi(x_i) - \sum_{ij} \alpha_i \alpha_j \Phi(x_i) \cdot \Phi(x_j)} \tag{2.4}$$

where α_i is Lagrange multiplier and $\Phi(x_i) \cdot \Phi(x_j)$ is inner product between $\Phi(x_i)$ and $\Phi(x_j)$.

In Equation 2.4, all mappings $\Phi(x)$ present only in inner products with other mappings. It is possible to define a new function of two input variables, called a kernel function: $K(x_i, x_j) = \Phi(x_i) \cdot \Phi(x_j)$ and replace all occurrences of $\Phi(x_i) \cdot \Phi(x_j)$ by this kernel. This results in:

$$\boldsymbol{L = \sum_i \alpha_i K(x_i, x_i) - \sum_{ij} \alpha_i \alpha_j K(x_i, x_j)} \tag{2.5}$$

where α_i is Lagrange multiplier and K is kernel function.

A good kernel function, which maps the target data onto a bounded, spherically shaped area in the feature space and outlier objects outside this area should be defined. In this case, the hypersphere model fits the data well and good classification performance is obtained.

In this study, we use a flexible data description with Gaussian kernel:

$$\boldsymbol{K(x_i, x_i) = \exp\left(\frac{\| x_i - x_j \|^2}{s^2}\right)}$$

Since $K(x_i, x_j) = 1$, both the Lagrangian and the evaluation function simplify. Ignoring constants Equation 2.5 becomes:

$$\boldsymbol{L = -\sum_{ij} \alpha_i \alpha_j K(x_i, x_j)} \tag{2.6}$$

From the solution of Equation 2.6, a new object z is labeled as target when Equation 2.7 is *true*.

$$\sum_i \alpha_i \exp\left(\frac{- \| z - x_i \|^2}{s^2}\right) > \frac{1}{2}(B - R^2) \tag{2.7}$$

where α_i is Lagrange multiplier and $B = 1 + \sum_{ij} \alpha_i \alpha_j K(x_i, x_j)$.
Note that B only depends on the support vectors x_i (not on the object z) and Equation 2.7 is a thresholded mixture of Gaussians.

The character of the data description depends on the value of the width parameter s. For very small values of s, differences between $K(x_i, x_j)$ for different i and j can be ignored, and the total model becomes a sum of equally weighted Gaussians, which is identical to a Parzen density estimation with a small width parameter. For very large values of s, values near or large than the maximum distance between objects, the flexible data description becomes the original spherical data description. For intermediate values of s, the data description of forms a weighted Parzen density. In Figure 2.4, on the left a small $s = 1.0$ width parameter is used, and on the right a large $s = 25.0$ is used (average nearest neighbor distance between the target objects is 1.1). In all cases, except when s becomes considerably large than the average distance, the description is tighter than the original spherical data description. Note that with increasing s the number of support vectors decreases.

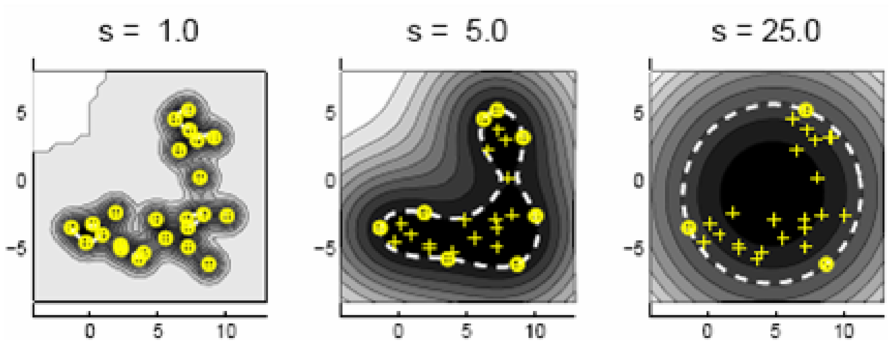


Figure 2.4: Impact of different width parameters values on a data description trained on a banana-shaped set. Support vectors are marked by circles.
Adapted from David M. Tax's thesis [15]

2.2.3.2 Parzen Density Estimation

The estimated density is a mixture of Gaussian kernels centered on the individual training objects, with diagonal covariance matrices $\sum_i = hI$

$$\boldsymbol{p_p(x) = \frac{1}{n}\sum_i p_N(x; x_i, hI)} \tag{2.8}$$

where p_N is Gaussian kernel, h is the kernel width parameter I is the identity matrix, n is the size of training set.

In Equation 2.8, kernel width h is equal in each feature direction meaning that the Parzen density estimator assumes equally weighted features and so it will be sensitive to the scaling of the feature values of the data, especially for lower sample sizes.

The only free parameter to train a Parzen density estimation is the optimal width of the kernel h, which is optimized using the maximum likelihood [11] on the training data set using leave-one-out. A good description totally depends on the representativeness of the training set i.e. a bad training set most probably results in a classifier with poor performance. The computational cost for training a Parzen density estimator is almost zero, but the test is expensive. All training objects have to be stored and, during test, distances to all training objects have to be calculated and sorted. This might severely limit the applicability of the method, especially when large datasets in high dimensional feature spaces are considered.

Chapter 3

Interactive Classification System Software

The software is mainly an integration of classification, feature extraction and visualization methods provided to the user for detecting geographical objects quickly and precisely in satellite images.

3.1 Software Design and Development Environment

Before the implementation phase several design decisions are taken and they are stated below.

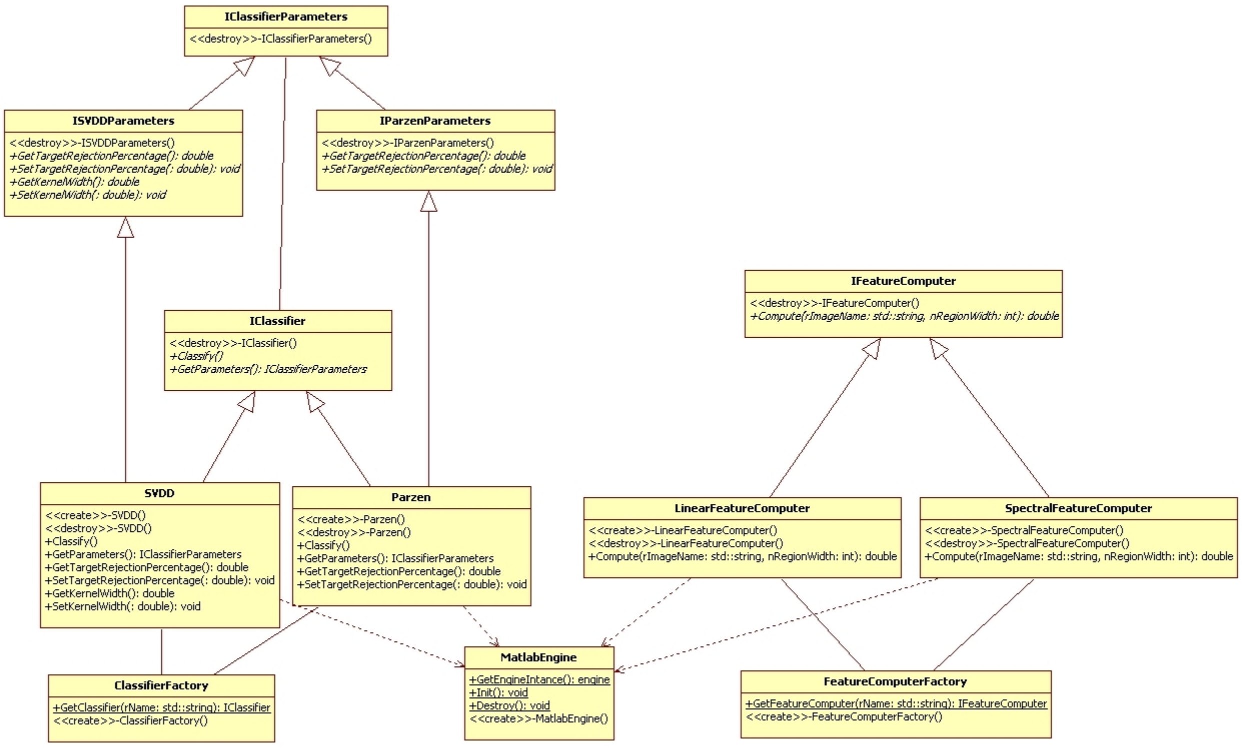
- Software should be open-source, and well documented for enabling potential contribution.
- Software should be cross-platform and run on at least *Linux* and *Windows* operating systems.
- Software should have an open architecture to allow addition of new classification and feature extraction methods.

In order to conform to the design decisions, cross platform graphical user interface (GUI) library *wxWidgets* written in *C++* is used. For code generation *gcc* is used on a *Windows* platform with the help of *MinGW*(Minimalist GNU for Windows). Eclipse is used as integrated development environment (IDE) since it can run on aimed platforms. With these development environment set, software can be maintained easily either on *Windows* or *Linux* platforms.

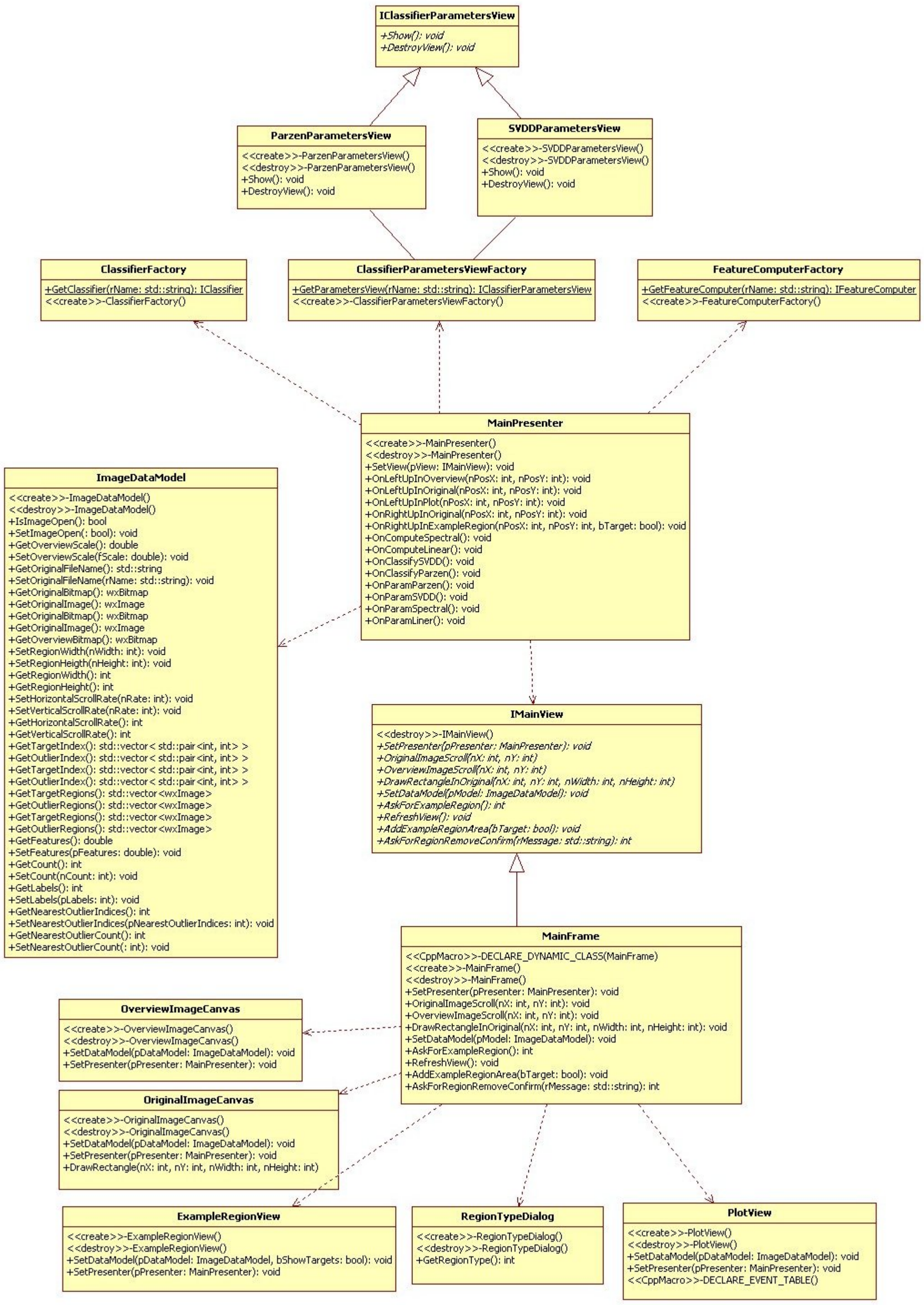
In this study, to develop an extendible software, an open architecture is employed. The architecture of the software is based on well-known design patterns. A general repeatable solution to commonly faced problems in software design is called a *design pattern* [6]. A design pattern is not a finished design that can be transformed directly into code. It is a description or template for how to solve a problem that can be used in many different situations. Design patterns can speed up the development process by providing tested, proven development paradigms. Effective software design requires considering issues that may not become visible until later in the implementation. Reusing design patterns helps to prevent subtle issues that can cause major problems and improves code readability for coders and architects familiar with the patterns. Design patterns can be classified in terms of the underlying problem they solve. Examples of problem-based pattern classifications include:

- Fundamental patterns,
- Creational patterns, which deal with the creation of objects,
- Structural patterns, which ease the design by identifying a simple way to realize relationships between entities,
- Behavioral patterns, which identify common communication patterns between objects and realize these patterns.

As a fundamental principle of object oriented design, interface pattern is used thoroughly. As seen from the class design of the software in Figure 3.1a and Figure 3.1b, classification, feature extraction classes are based on interface classes. From creational patterns, *Factory* [8] pattern is employed for creation of specific implementations (SVDD, Parzen density estimation, SVM)of these interfaces. With this design decision, graphical user interface (GUI) classes have no direct connection to the specific implementations of *IClassifier* and *IFeatureComputer* interfaces. Factory classes *FeatureComputerFactory*, *ClassifierFactory* provide implicit access to the functions of the implementation classes. For the GUI architecture, Model-View-Presenter (MVP) [12] architectural pattern is employed, which proposes logic free *view* classes controlled by *presenter* classes through view interfaces. This will help the developer easily to change the view classes or even the GUI library without any modification to the presenter classes, which contain the logical code.


IClassifierParameters
<<destroy>>-IClassifierParameters()
ISVDDParameters
<<destroy>>-ISVDDParameters()
+GetTargetRejectionPercentage(): double
+SetTargetRejectionPercentage(: double): void
+GetKernelWidth(): double
+SetKernelWidth(: double): void
IParzenParameters
<<destroy>>-IParzenParameters()
+GetTargetRejectionPercentage(): double
+SetTargetRejectionPercentage(: double): void
IClassifier
<<destroy>>-IClassifier()
+Classify()
+GetParameters(): IClassifierParameters
IFeatureComputer
<<destroy>>-IFeatureComputer()
+Compute(rImageName: std::string, nRegionWidth: int): double
SVDD
<<create>>-SVDD()
<<destroy>>-SVDD()
+Classify()
+GetParameters(): IClassifierParameters
+GetTargetRejectionPercentage(): double
+SetTargetRejectionPercentage(: double): void
+GetKernelWidth(): double
+SetKernelWidth(: double): void
Parzen
<<create>>-Parzen()
<<destroy>>-Parzen()
+Classify()
+GetParameters(): IClassifierParameters
+GetTargetRejectionPercentage(): double
+SetTargetRejectionPercentage(: double): void
LinearFeatureComputer
<<create>>-LinearFeatureComputer()
<<destroy>>-LinearFeatureComputer()
+Compute(rImageName: std::string, nRegionWidth: int): double
SpectralFeatureComputer
<<create>>-SpectralFeatureComputer()
<<destroy>>-SpectralFeatureComputer()
+Compute(rImageName: std::string, nRegionWidth: int): double
MatlabEngine
+GetEngineIntance(): engine
+Init(): void
+Destroy(): void
<<create>>-MatlabEngine()
ClassifierFactory
+GetClassifier(rName: std::string): IClassifier
<<create>>-ClassifierFactory()
FeatureComputerFactory
+GetFeatureComputer(rName: std::string): IFeatureComputer
<<create>>-FeatureComputerFactory()

(a) Classifier Class Design


IClassifierParametersView
+Show(): void
+DestroyView(): void
ParzenParametersView
<<create>>-ParzenParametersView()
<<destroy>>-ParzenParametersView()
+Show(): void
+DestroyView(): void
SVDDParametersView
<<create>>-SVDDParametersView()
<<destroy>>-SVDDParametersView()
+Show(): void
+DestroyView(): void
ClassifierFactory
+GetClassifier(rName: std::string): IClassifier
<<create>>-ClassifierFactory()
ClassifierParametersViewFactory
+GetParametersView(rName: std::string): IClassifierParametersView
<<create>>-ClassifierParametersViewFactory()
FeatureComputerFactory
+GetFeatureComputer(rName: std::string): IFeatureComputer
<<create>>-FeatureComputerFactory()
MainPresenter
<<create>>-MainPresenter()
<<destroy>>-MainPresenter()
+SetView(pView: IMainView): void
+OnLeftUpInOverview(nPosX: int, nPosY: int): void
+OnLeftUpInOriginal(nPosX: int, nPosY: int): void
+OnLeftUpInPlot(nPosX: int, nPosY: int): void
+OnRightUpInOriginal(nPosX: int, nPosY: int): void
+OnRightUpInExampleRegion(nPosX: int, nPosY: int, bTarget: bool): void
+OnComputeSpectral(): void
+OnComputeLinear(): void
+OnClassifySVDD(): void
+OnClassifyParzen(): void
+OnParamParzen(): void
+OnParamSVDD(): void
+OnParamSpectral(): void
+OnParamLiner(): void
ImageDataModel
<<create>>-ImageDataModel()
<<destroy>>-ImageDataModel()
+IsImageOpen(): bool
+SetImageOpen(: bool): void
+GetOverviewScale(): double
+SetOverviewScale(fScale: double): void
+GetOriginalFileName(): std::string
+SetOriginalFileName(rName: std::string): void
+GetOriginalBitmap(): wxBitmap
+GetOriginalImage(): wxImage
+GetOriginalBitmap(): wxBitmap
+GetOriginalImage(): wxImage
+GetOverviewBitmap(): wxBitmap
+SetRegionWidth(nWidth: int): void
+SetRegionHeigth(nHeight: int): void
+GetRegionWidth(): int
+GetRegionHeight(): int
+SetHorizontalScrollRate(nRate: int): void
+SetVerticalScrollRate(nRate: int): void
+GetHorizontalScrollRate(): int
+GetVerticalScrollRate(): int
+GetTargetIndex(): std::vector< std::pair<int, int> >
+GetOutlierIndex(): std::vector< std::pair<int, int> >
+GetTargetIndex(): std::vector< std::pair<int, int> >
+GetOutlierIndex(): std::vector< std::pair<int, int> >
+GetTargetRegions(): std::vector<wxImage>
+GetOutlierRegions(): std::vector<wxImage>
+GetTargetRegions(): std::vector<wxImage>
+GetOutlierRegions(): std::vector<wxImage>
+GetFeatures(): double
+SetFeatures(pFeatures: double): void
+GetCount(): int
+SetCount(nCount: int): void
+GetLabels(): int
+SetLabels(pLabels: int): void
+GetNearestOutlierIndices(): int
+SetNearestOutlierIndices(pNearestOutlierIndices: int): void
+GetNearestOutlierCount(): int
+SetNearestOutlierCount(: int): void
IMainView
<<destroy>>-IMainView()
+SetPresenter(pPresenter: MainPresenter): void
+OriginalImageScroll(nX: int, nY: int)
+OverviewImageScroll(nX: int, nY: int)
+DrawRectangleInOriginal(nX: int, nY: int, nWidth: int, nHeight: int)
+SetDataModel(pModel: ImageDataModel): void
+AskForExampleRegion(): int
+RefreshView(): void
+AddExampleRegionArea(bTarget: bool): void
+AskForRegionRemoveConfirm(rMessage: std::string): int
MainFrame
<<CppMacro>>-DECLARE_DYNAMIC_CLASS(MainFrame)
<<create>>-MainFrame()
<<destroy>>-MainFrame()
+SetPresenter(pPresenter: MainPresenter): void
+OriginalImageScroll(nX: int, nY: int): void
+OverviewImageScroll(nX: int, nY: int): void
+DrawRectangleInOriginal(nX: int, nY: int, nWidth: int, nHeight: int): void
+SetDataModel(pModel: ImageDataModel): void
+AskForExampleRegion(): int
+RefreshView(): void
+AddExampleRegionArea(bTarget: bool): void
+AskForRegionRemoveConfirm(rMessage: std::string): int
OverviewImageCanvas
<<create>>-OverviewImageCanvas()
<<destroy>>-OverviewImageCanvas()
+SetDataModel(pDataModel: ImageDataModel): void
+SetPresenter(pPresenter: MainPresenter): void
OriginalImageCanvas
<<create>>-OriginalImageCanvas()
<<destroy>>-OriginalImageCanvas()
+SetDataModel(pDataModel: ImageDataModel): void
+SetPresenter(pPresenter: MainPresenter): void
+DrawRectangle(nX: int, nY: int, nWidth: int, nHeight: int)
ExampleRegionView
<<create>>-ExampleRegionView()
<<destroy>>-ExampleRegionView()
+SetDataModel(pDataModel: ImageDataModel, bShowTargets: bool): void
+SetPresenter(pPresenter: MainPresenter): void
RegionTypeDialog
<<create>>-RegionTypeDialog()
<<destroy>>-RegionTypeDialog()
+GetRegionType(): int
PlotView
<<create>>-PlotView()
<<destroy>>-PlotView()
+SetDataModel(pDataModel: ImageDataModel): void
+SetPresenter(pPresenter: MainPresenter): void
<<CppMacro>>-DECLARE_EVENT_TABLE()

(b) Graphical User Interface Class Design

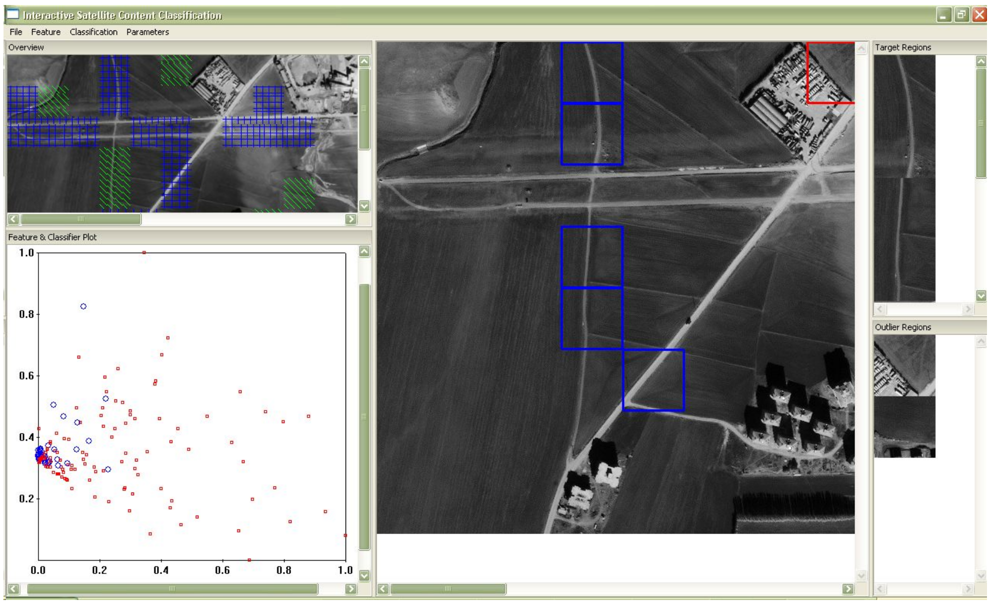
Figure 3.1: Class design of the interactive classification system software.

3.2 Software Description

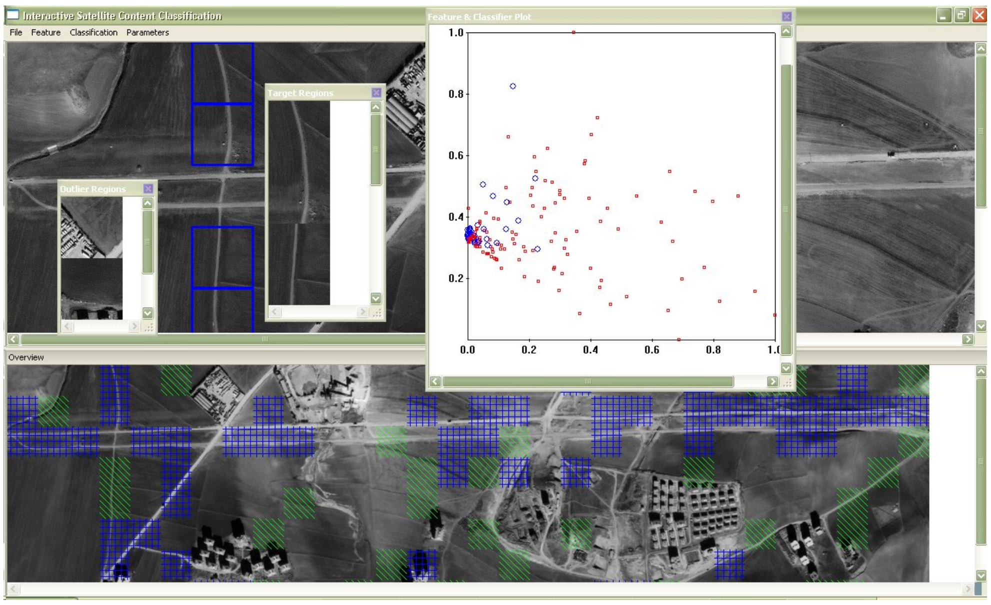
For the demonstration of the ideas of this study, we implemented an interactive classification software. GUI parts of the software was developed using wxWidgets [13] framework with C++ programming language. Dockable GUI elements from wxWidgets framework were employed in order to provide an easily customizable interface for users as shown in Figure 3.2. One class classification and feature computation algorithms were implemented with Matlab using ddtools [16], prtools [7] and integrated to the software through Matlab C external interface libraries. Code parts, which are interacting with the Matlab, were hidden in one class classifier implementations, hence Matlab dependency was minimized. Finally for binary classification libsvm [2] was used in a similar way to usage of Matlab for one class classification. Main functionalities provided by our classification software are given below.

- Several image formats including JPEG, BMP, PNG, GIF, PCX, TIF and XPM are supported for processing.
- Algorithms for extracting spectral features and linear features described in Section 2.1.1 and Section 2.1.2, respectively are available.
- As one class classifiers, SVDD and Parzen density estimation are available in addition to the SVM classifier, which can be used by the user as well.
- A half size overview image is displayed, for helping user to navigate through large images easily. This overview and original size image is linked together, such that whenever user selects a point in overview or original image view, the other view is automatically scrolled to the selected point.
- A plot view is presented to the user for displaying features or multidimensional scaled features (in case of high dimensional features). The plot view is also linked to the original image view such that, whenever a point in feature space is selected the original image is scrolled automatically to the region having the feature which is closest to the selected point in feature space.

- The list of target and outlier examples are displayed in separate views, which are interactively managed by the user through the interface.
- Parameters of classifiers can be changed easily from the parameter views provided for each classifier.
- Classification results are shown in a separate layer on the overview image. In addition, features from target and outlier objects are labeled differently in the plot view when classification is performed.
- It is possible for user to save classification results or training set information for resuming classification process in another time.



(a) Docked interface - dialogs



(b) Floating interface - dialogs

Figure 3.2: Interface of the interactive classification software.

Chapter 4

Experiments And Results

4.1 Description of The System

The main idea behind the system is to get user feedback and iteratively improve the performance of the classifier. First step in the classification process is generation of the initial set containing example target objects. This initial set contains only target objects. The result of the classification is subsequently presented to the user with nearest outliers highlighted. Nearest outliers to the target data description have the most valuable information to tighten the boundary around the target distribution. User adds more examples (target or outlier) to the training set and the target data description is re-computed. This process is proceeded with the support vector data description (SVDD) until a preset training set size is achieved or the user selects to another classifier, Parzen density estimation or SVM. In the first iterations, SVDD is preferred to Parzen density estimation and SVM, because the latter classifiers require a larger training set than SVDD. In addition, Parzen density estimation and SVM produce poor results in case of a bad representative training set, which is more likely to happen in early iterations.

4.2 Prototype Design and Experiment

The prototype is an exact copy of the proposed interactive system except the graphical user interface (GUI) parts. User interaction is simulated by a series of predefined labels given to image regions containing the target object and outlier objects. After each iteration, size of the training set is increased and the classifier is re-run. The boundary around the target data description and nearest outliers to the classifier boundary is presented to the user for feedback. At the end of each iteration, classifier performance is compared against the ground truth data existing with the example satellite image.

The aim of the prototyping is to prove that the method will work as it is designed. Therefore we decided to make two experiments; the first experiment is with simple spectral features of intensity values while the second experiment is based on linear features.

First experiment is aimed at detection of urban areas in a satellite image with existing ground truth data. The satellite image given in Figure 4.1 is split into 1500 regions of size 80×80 pixels and 231 of these regions are labeled as urban area by an expert. One of the reasons for using spectral features is that they are simple, easy to calculate and produce good results for urban area targets in gray level images. Parzen density estimation is preferred to SVM in this experiment, since the dimension of the spectral features is just two.

Second experiment is aimed at proving that our approach produces good results, in case of high dimensional feature space. Regions which contain main roads in satellite image given in Figure 4.2 are to be detected. The image is split into 450 regions and 127 of these regions are labeled as road by an expert. SVM is preferred to Parzen density estimation in this experiment, since the latter requires a complete density estimate in complete feature space and in cases like this when high dimensional feature spaces are present, this classifier requires huge amount of data.

The notations used in interactive classification algorithm of the prototype is given as follows;

- I : input satellite image,
- μ : mean of an image region in I,
- σ : standard deviation of an image region in I,
- H : linear segment histogram of an image region in I,
- ω : classifier,
- Λ : set of all image regions in I,
- Λ_{train} : set of image regions in I used in training of ω.

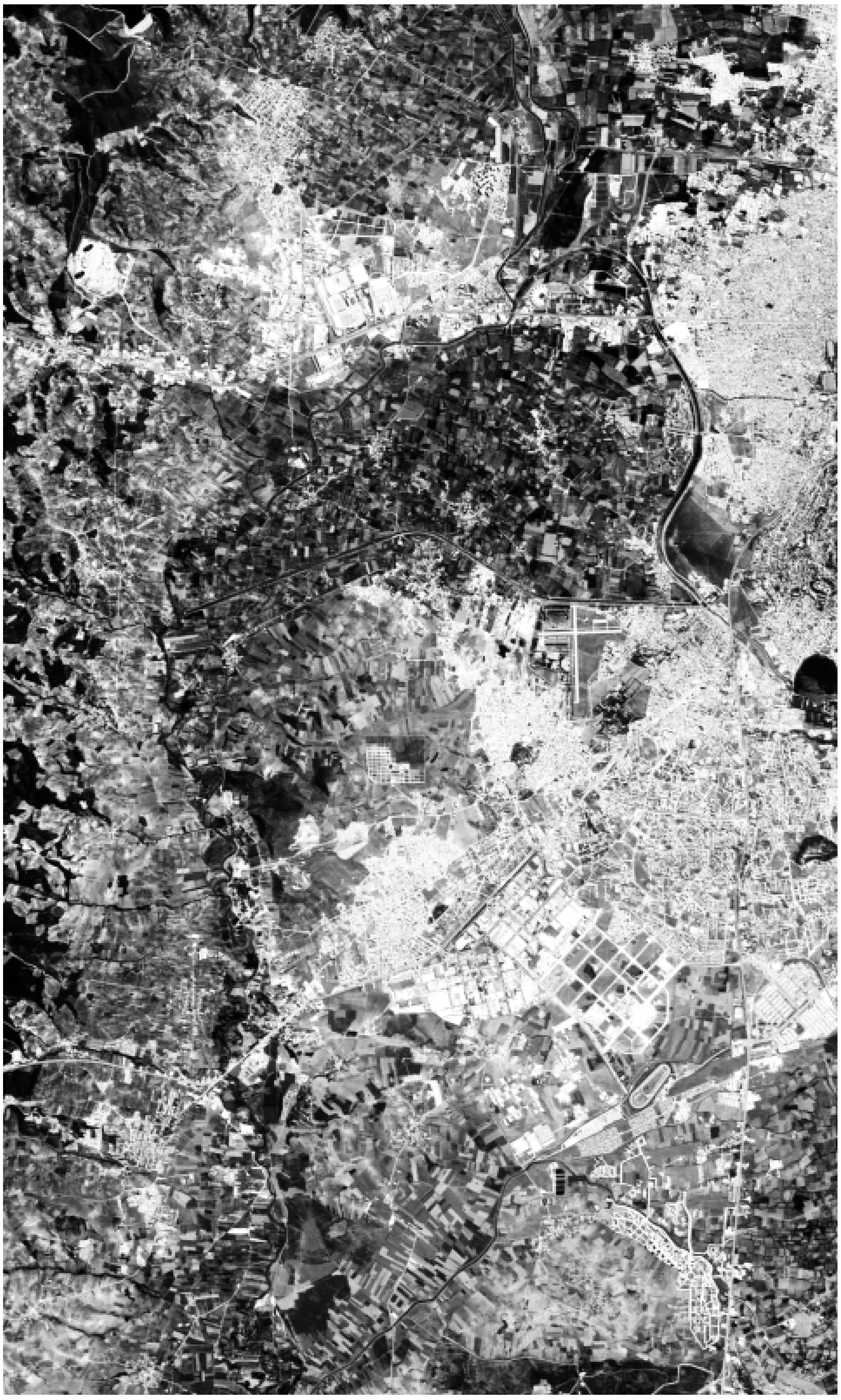


Figure 4.1: Prototype experiment image: single band SPOT panchromatic image of size (2400×4000) with a spatial resolution of $10m$.

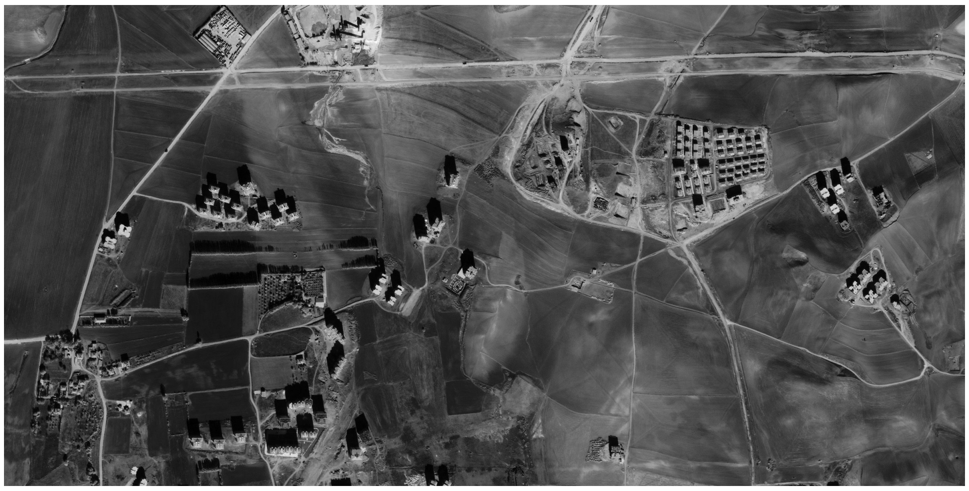


Figure 4.2: Prototype experiment image: single band SPOT panchromatic image of size (2400×1200) with a spatial resolution of $10m$.

The classification algorithms used, follows the approach given in Section 4.1. The steps of the algorithms for urban area detection and road detection are given in Algorithm 4 and Algorithm 5 respectively.

Algorithm 4 Classification Using Spectral Features

```
1: for all image regions $i$ in $\Lambda$ do
2:    calculate $\mu_i$ and $\sigma_i$
3: end for
4: set $\omega = SVDD$
5: get $\Lambda_{train}$ from user
6: repeat
7:    set $\omega$ parameters
8:    train $\omega$ with $\Lambda_{train}$
9:    apply $\omega$ to $\Lambda$
10:   show $I$
11:   mark classified target objects on $I$
12:   mark $\Lambda_{train}$ on $I$
13:   mark nearest outliers on $I$
14:   show $\omega$ performance against ground truth information
15:   user adds new target and outlier objects to $\Lambda_{train}$
16:   if user request classifier change then
17:      $\omega = Parzen\ density\ estimation$
18:   end if
19: until user stops iteration
```

Algorithm 5 Classification Using Linear Features

```
1: for all image regions $i$ in $\Lambda$ do
2:     calculate $H$
3: end for
4: set $\omega = SVDD$
5: get $\Lambda_{train}$ from user
6: repeat
7:     set $\omega$ parameters
8:     train $\omega$ with $\Lambda_{train}$
9:     apply $\omega$ to $\Lambda$
10:    show $I$
11:    mark classified target objects on $I$
12:    mark $\Lambda_{train}$ on $I$
13:    mark nearest outliers on $I$
14:    show $\omega$ performance against ground truth information
15:    user adds new target and outlier objects to $\Lambda_{train}$
16:    if user request classifier change then
17:        $\omega = SVM$
18:    end if
19: until user stops iteration
```

The experiment for detecting urban areas consists of two runs of five iterations with increasing training set size. At the end of the each iteration, the results are presented visually on experiment image by using markers defined in Table 4.1 and classifier boundary around the features is plotted.

The experiment for detecting areas containing roads consists of two runs of six iterations with increasing training set size. At the end of the each iteration, the results are presented visually on experiment image and multidimensional scaling is performed for displaying results on scaled features. Since used linear features are ten dimensional, classifier boundary cannot be plotted.

Table 4.1: Prototype experiment: markers for objects used on experiment image.

Marker Definition	Marker Symbol
All targets from ground truth data	□
Targets in training set	+
Outliers in training set	+
Detected targets	x
Nearest outliers	o

Performance of the classification is evaluated by the criteria defined below:

True positives: *number of correctly detected targets*

False positives: *number of outliers detected as targets*

True negatives: *number of correctly detected outliers*

False negatives: *number of targets detected as outliers*

Precision:

$$\frac{true\,positives}{true\,positives\;+\;false\,positives}$$

Recall:

$$\frac{true\,positives}{true\,positives\;+\;false\,negatives}$$

In the urban area experiment, for the first run SVDD is used with given training set size and parameters in Table 4.2, and for the second run we use the training set generated during the first run and Parzen density estimation with parameters given in Table 4.3. Image regions in the initial training set are given in Figure 4.3. Targets and outliers corrected by the user after first iteration are given in Figure 4.4 and Figure 4.5, respectively. Results for SVDD and Parzen density estimation on the experiment image are given in Figure 4.9 and Figure 4.10, respectively. Performance of SVDD and Parzen density estimation can be visualized in Figure 4.11 and Figure 4.12, respectively.

In the road experiment, for the first run SVDD is used with given training set size and parameters in Table 4.4, and for the second run we use the training set generated during the first run and SVM classifier with parameters given in Table 4.5. Image regions in the initial training set are given in Figure 4.6. Targets and outliers corrected by the user after first iteration are given in Figure 4.7 and Figure 4.8, respectively. Results for SVDD and SVM classifiers on the experiment image are given in Figure 4.13 and Figure 4.14, respectively. Performance of SVDD and SVM classifiers can be visualized in Figure 4.15 and Figure 4.16, respectively.

Table 4.2: Prototype experiment 1: SVDD parameters in urban area experiment iterations.

Iteration number	Target rejection rate	# of support vectors	Kernel width	# of target examples	# of outlier examples
1	0.1	3	1	10	0
2	0.1	9	0.9	18	5
3	0.1	11	0.6	23	10
4	0.1	18	0.5	27	14
5	0.1	27	0.51	30	20

Table 4.3: Prototype experiment 1: Parzen density estimation parameters in urban area experiment iterations.

Iteration number	Target rejection rate	Width	# of target examples	# of outlier examples
1	0.1	0.060	10	0
2	0.1	0.107	18	5
3	0.15	0.094	23	10
4	0.15	0.085	27	14
5	0.15	0.086	30	20

Table 4.4: Prototype experiment 2: SVDD parameters in road experiment iterations.

Iteration number	Target rejection rate	# of support vectors	Kernel width	# of target examples	# of outlier examples
1	0.1	4	0.6	10	0
2	0.1	14	1.4	22	7
3	0.1	19	0.9	32	17
4	0.1	28	0.8	42	22
5	0.05	26	0.8	54	22
6	0.05	32	0.8	67	34

Table 4.5: Prototype experiment 2: SVM parameters in road experiment iterations.

Iteration number	Gamma	C	# of support vectors	# of target examples	# of outlier examples
1	8	128	0	10	0
2	8	128	20	22	7
3	8	128	30	32	17
4	8	128	35	42	22
5	8	128	38	54	22
6	8	128	62	67	34

Table 4.6: Prototype experiment 1: SVDD performance observed in urban area experiment iterations.

Iteration number	True positives	False positives	True negatives	False negatives	Precision	Recall
1	173	105	1164	58	0.62	0.75
2	199	182	1087	32	0.49	0.86
3	213	124	1145	18	0.63	0.92
4	213	111	1158	18	0.66	0.92
5	211	100	1169	20	0.68	0.91

Table 4.7: Prototype experiment 1: Parzen density estimation performance observed in urban area experiment iterations.

Iteration number	True positives	False positives	True negatives	False negatives	Precision	Recall
1	190	77	1192	41	0.71	0.82
2	226	239	1030	5	0.49	0.97
3	226	168	1101	5	0.57	0.98
4	225	190	1079	6	0.54	0.97
5	225	150	1119	6	0.60	0.97

In Parzen density estimation method, target rejection rate is used for finding the required threshold to reject lowest given fraction of the targets in the training data set. In addition, in SVDD target rejection rate together with the kernel width affects the number of support vectors identifying the data description [15].

Table 4.8: Prototype experiment 2: SVDD performance observed in road experiment iterations.

Iteration number	True positives	False positives	True negatives	False negatives	Precision	Recall
1	69	72	251	58	0.49	0.54
2	90	85	238	37	0.51	0.71
3	93	85	238	34	0.52	0.73
4	100	80	243	27	0.56	0.79
5	107	91	232	20	0.54	0.84
6	108	96	227	19	0.54	0.85

Table 4.9: Prototype experiment 2: SVM performance observed in road experiment iterations.

Iteration number	True positives	False positives	True negatives	False negatives	Precision	Recall
1	127	323	0	0	0.28	1.00
2	101	93	230	26	0.52	0.80
3	110	120	203	17	0.48	0.87
4	109	107	216	18	0.50	0.86
5	115	126	197	12	0.48	0.90
6	116	77	246	11	0.60	0.91

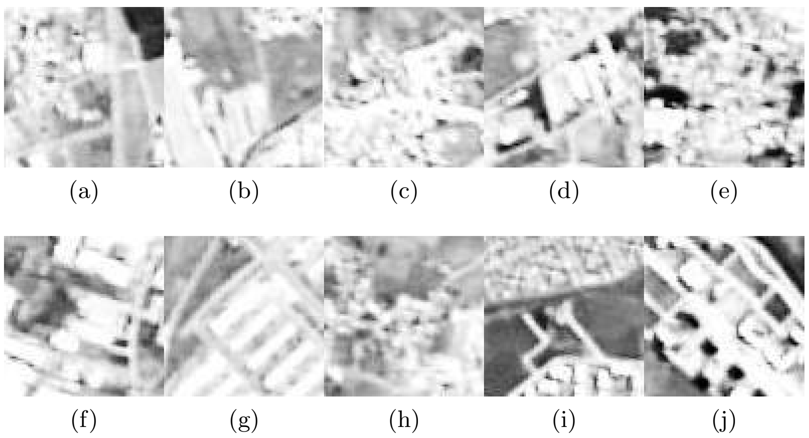


Figure 4.3: Initial training set for urban area experiment (Prototype experiment 1) containing 10 target objects.

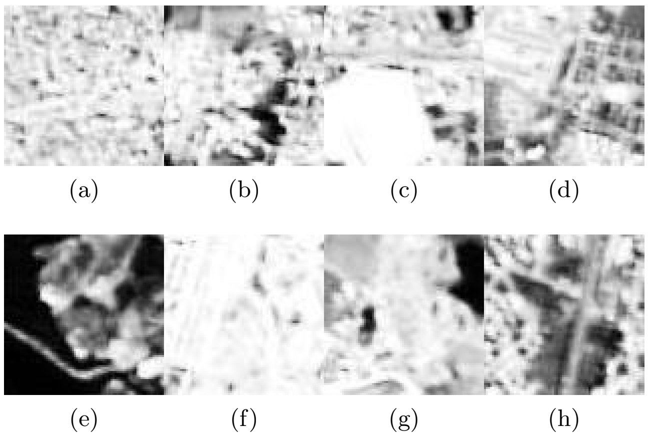


Figure 4.4: Targets corrected by the user at the end of the first iteration of urban area experiment (Prototype experiment 1). Corrected targets are added to the training set.

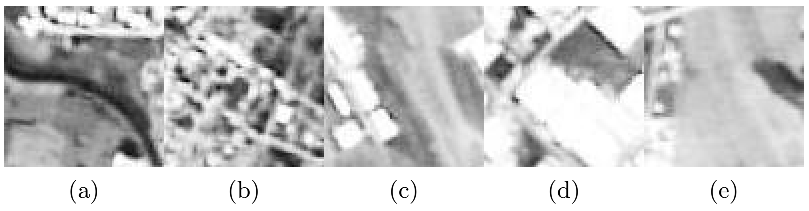


Figure 4.5: Outliers corrected by the user at the end of the first iteration of urban area experiment (Prototype experiment 1). Corrected outliers are added to the training set.

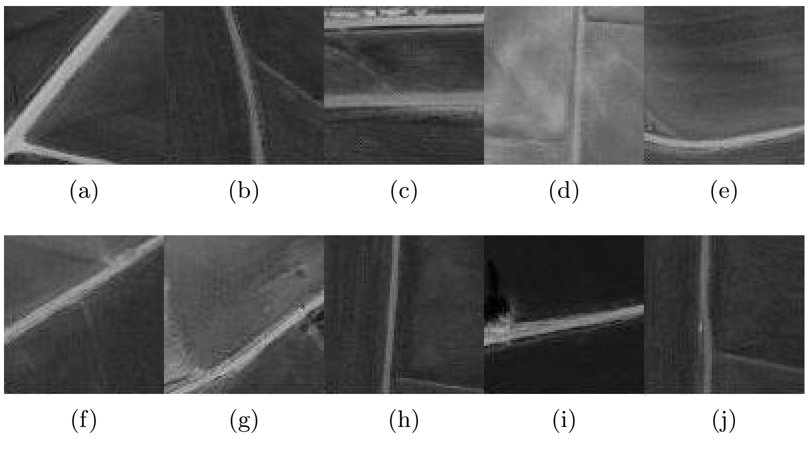


Figure 4.6: Initial training set for road experiment (Prototype experiment 2) containing 10 target objects.

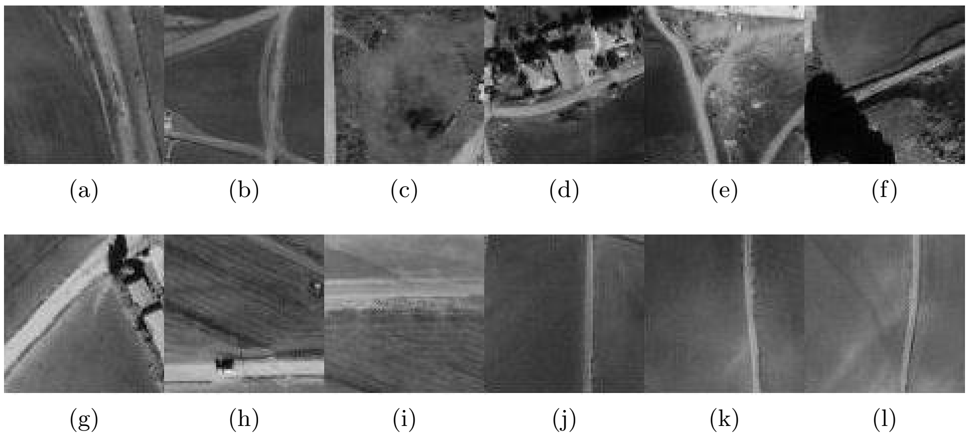


Figure 4.7: Targets corrected by the user at the end of the first iteration of road experiment (Prototype experiment 2). Corrected targets are added to the training set.

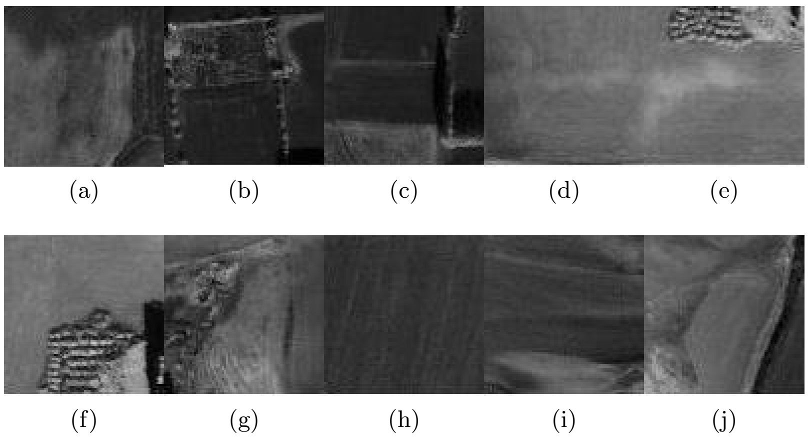
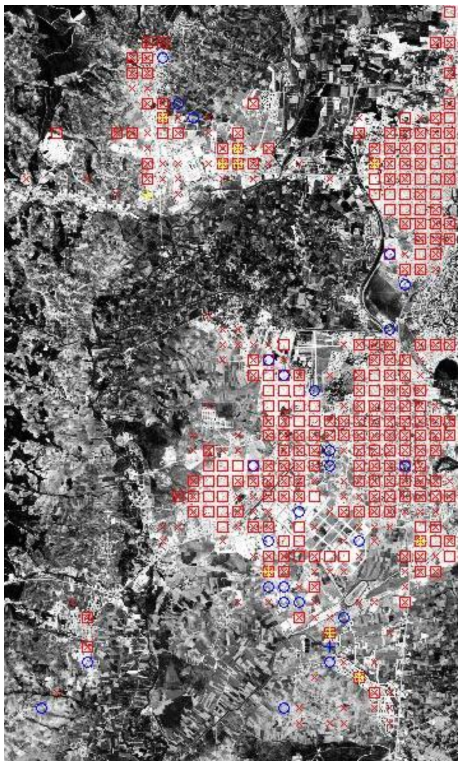
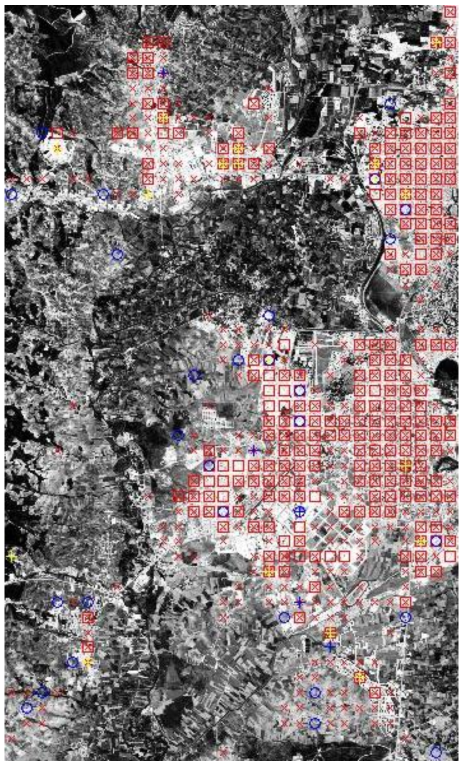
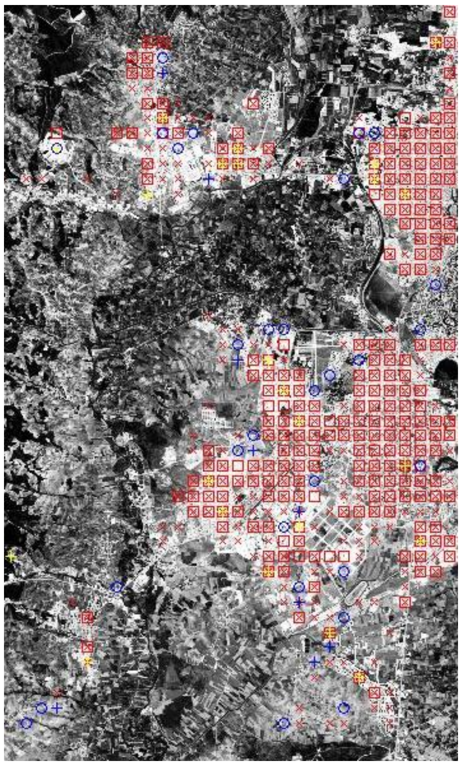
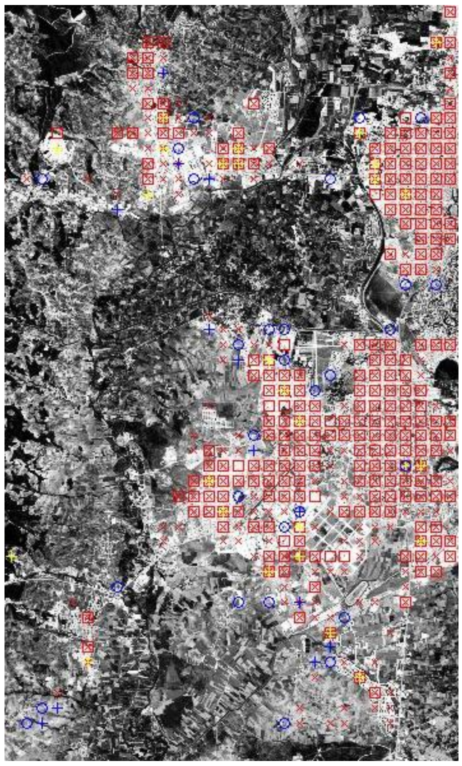


Figure 4.8: Outliers corrected by the user at the end of the first iteration of road experiment (Prototype experiment 2). Corrected outliers are added to the training set.


(a) 1st Iteration


(b) 2nd Iteration


(c) 3rd Iteration


(d) 4th Iteration

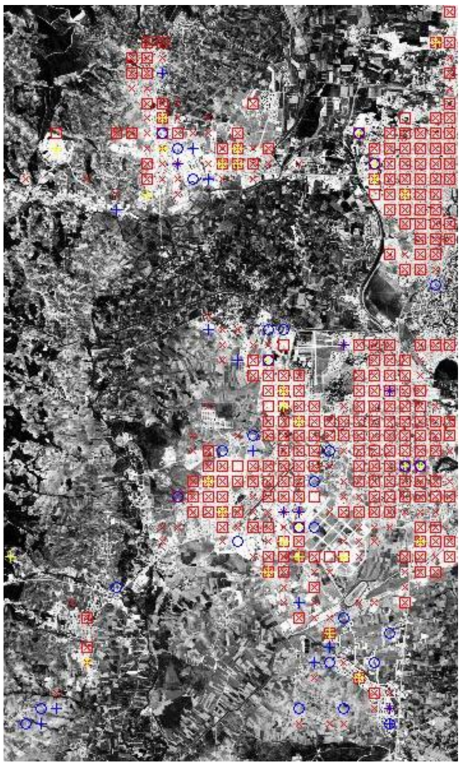
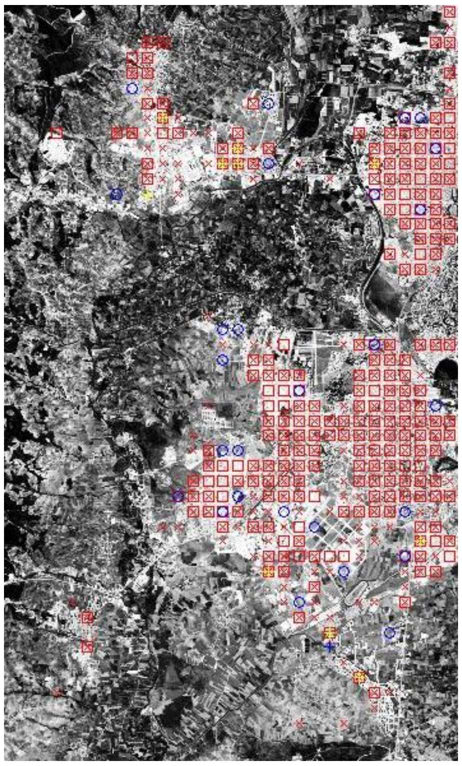
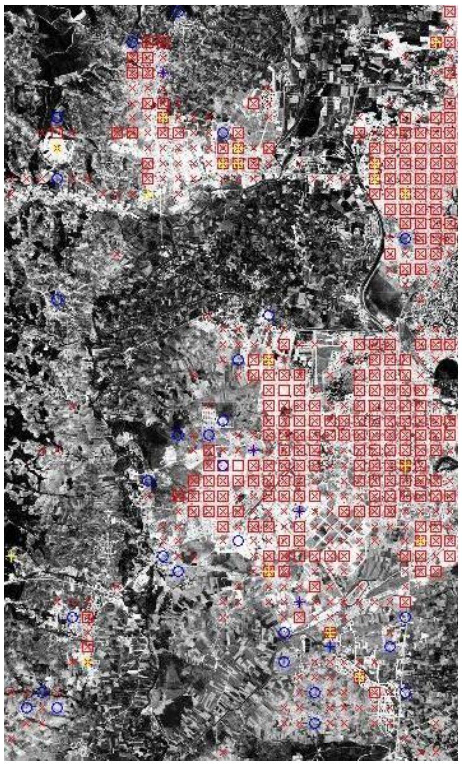
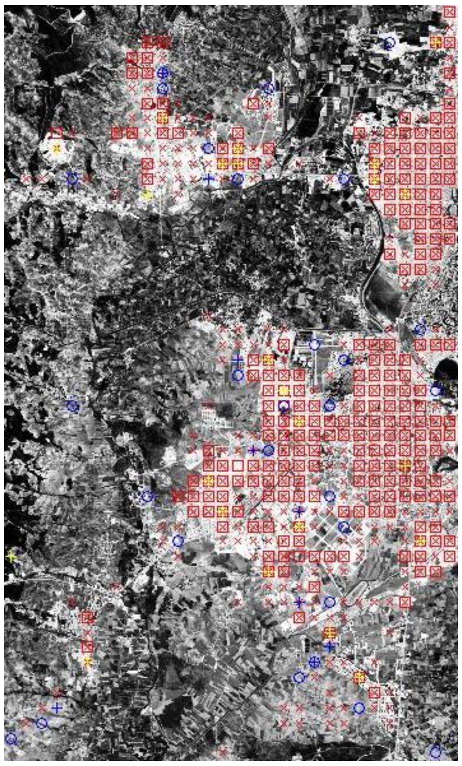
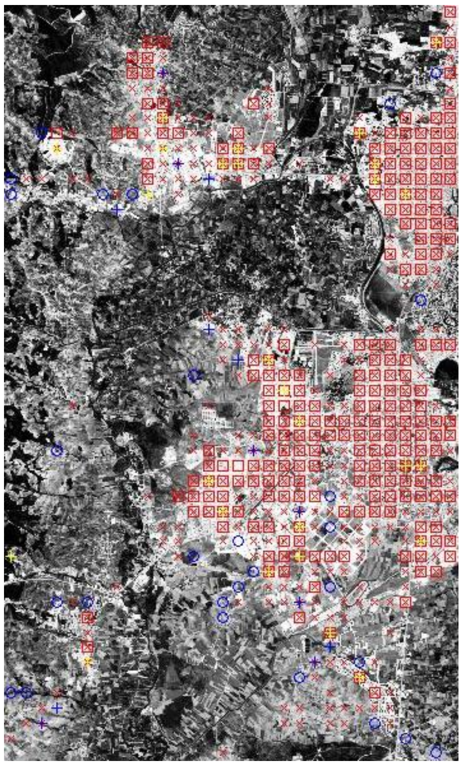

(e) 5th Iteration

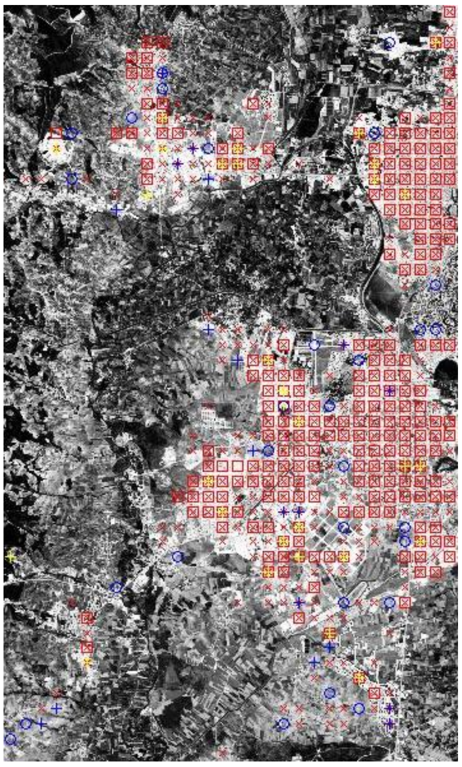
Figure 4.9: Detected targets, training set and ground truth information on experiment image in iterations of the run with SVDD for urban area experiment (Prototype experiment 1).


(a) 1st Iteration


(b) 2nd Iteration

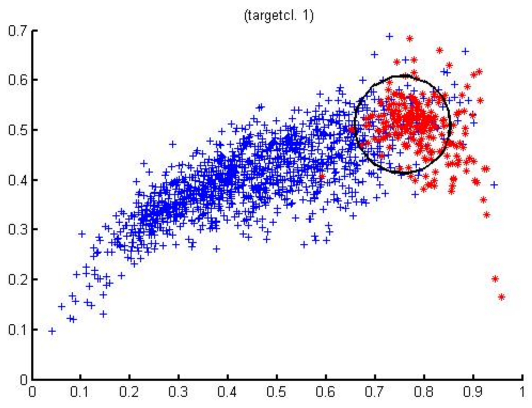

(c) 3rd Iteration


(d) 4th Iteration

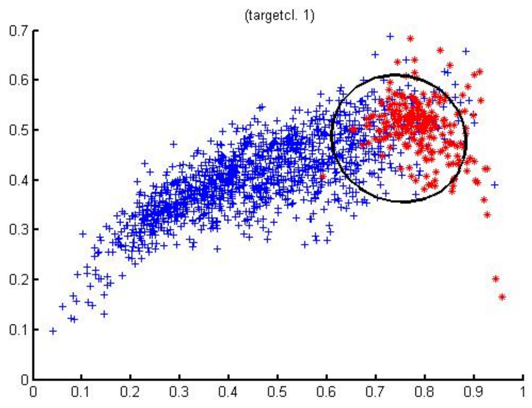


(e) 5th Iteration

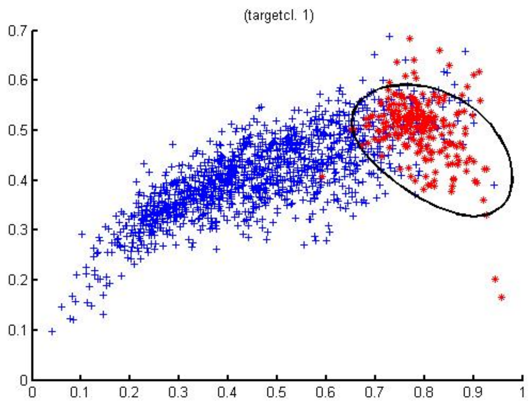
Figure 4.10: Detected targets, training set and ground truth information on experiment image in iterations of the run with Parzen density estimation for urban area experiment (Prototype experiment 1).



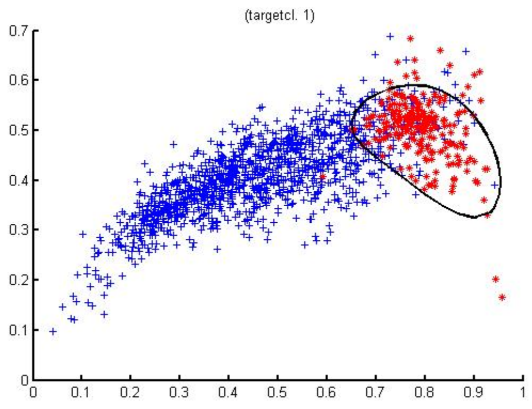
(a) 1st Iteration



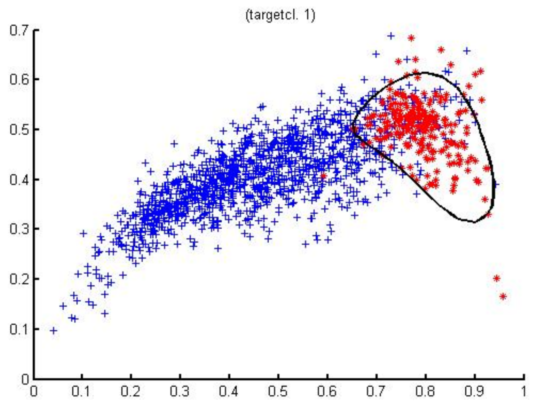
(b) 2nd Iteration



(c) 3rd Iteration

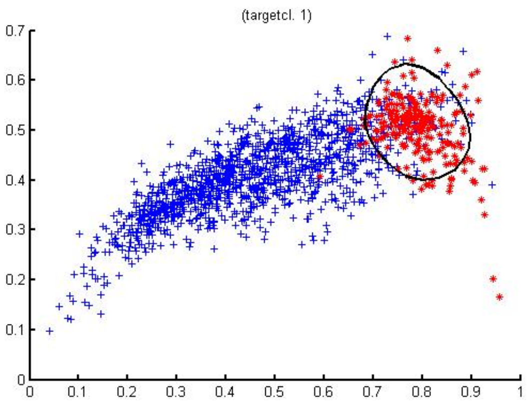


(d) 4th Iteration

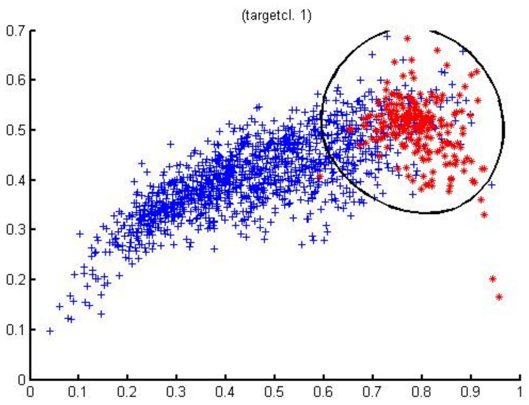


(e) 5th Iteration

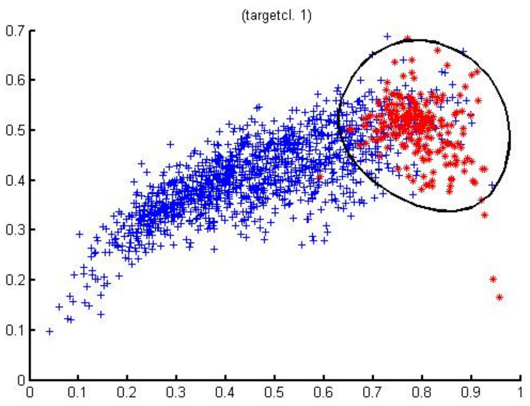
Figure 4.11: SVDD classifiers, formed in iterations of urban area experiment (Prototype experiment 1), shown in feature space. Outliers marked with $+$ and targets with $*$.



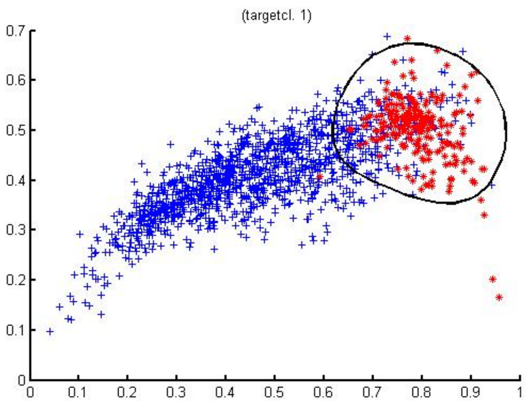
(a) 1st Iteration



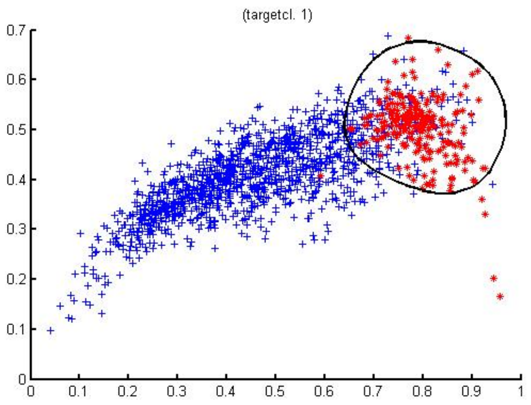
(b) 2nd Iteration



(c) 3rd Iteration

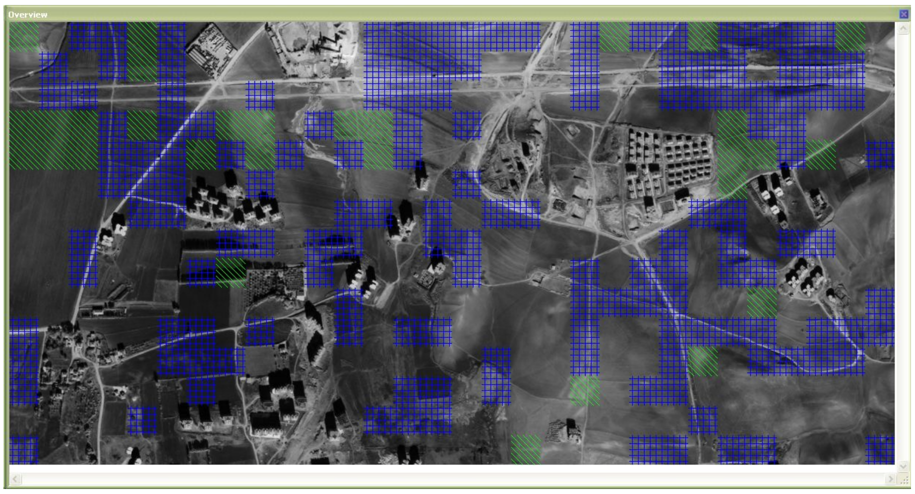


(d) 4th Iteration

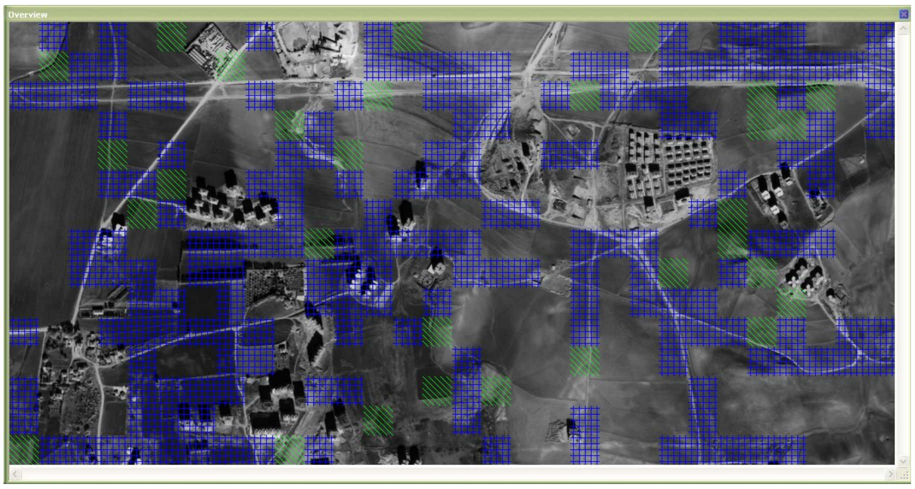


(e) 5th Iteration

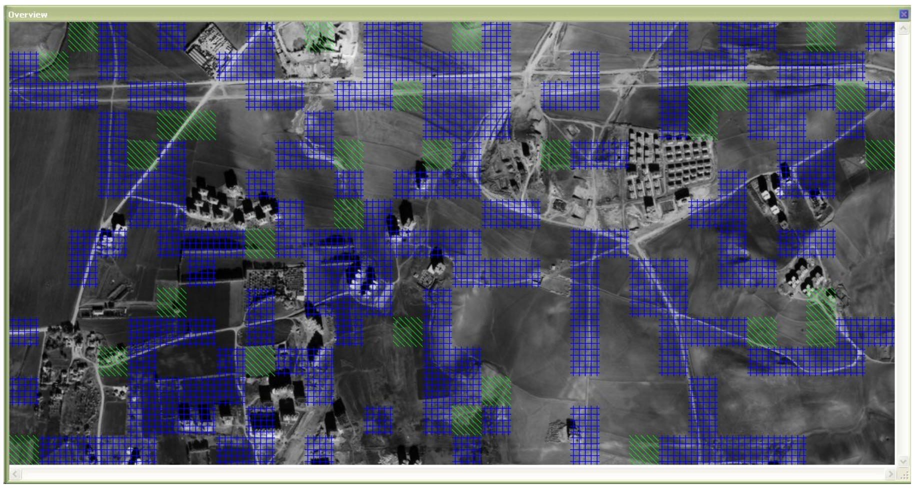
Figure 4.12: Parzen density estimation classifiers, formed in iterations of urban area experiment (Prototype experiment 1), shown in feature space. Outliers marked with $+$ and targets with $*$.



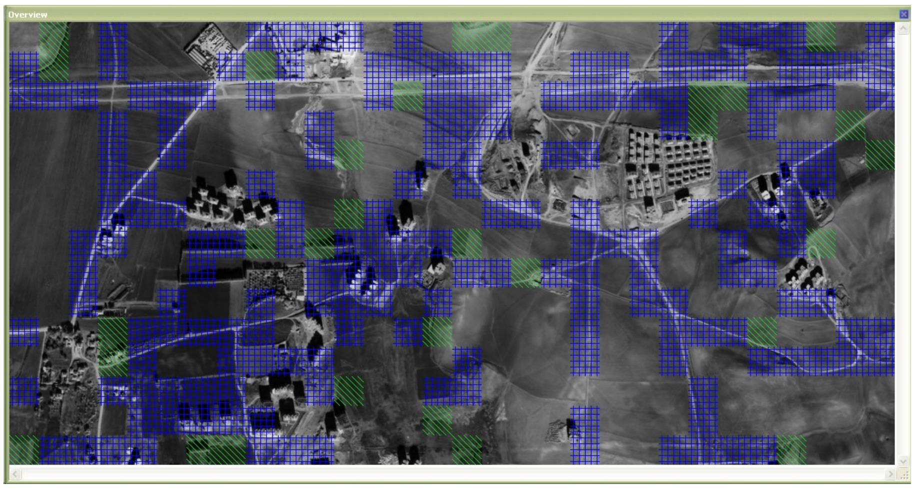
(a) 1^{st} Iteration



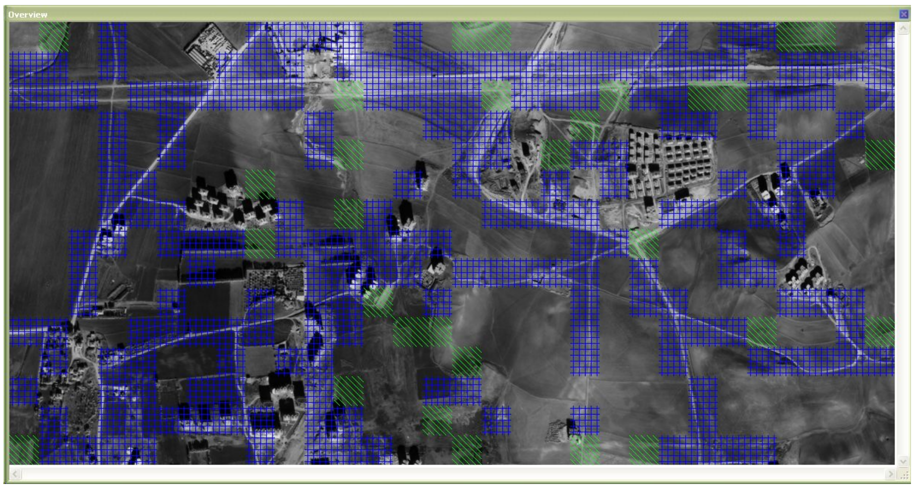
(b) 2^{nd} Iteration



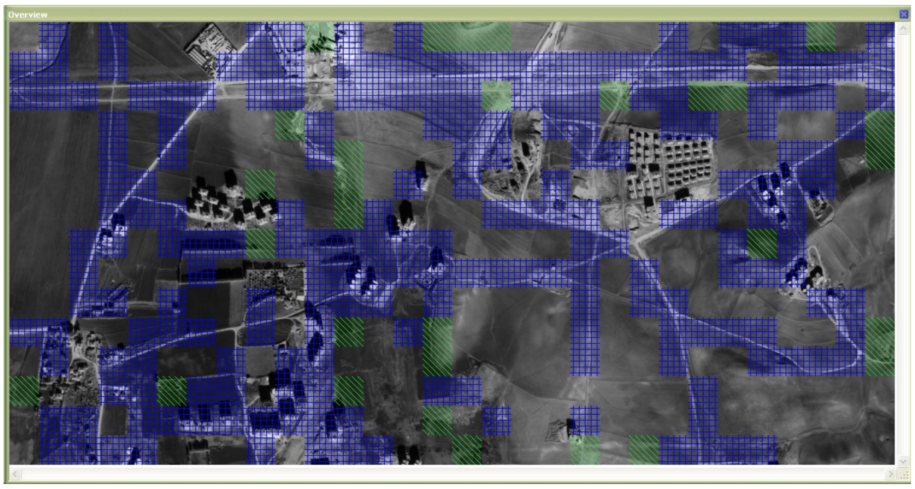
(c) 3^{rd} Iteration



(d) 4th Iteration

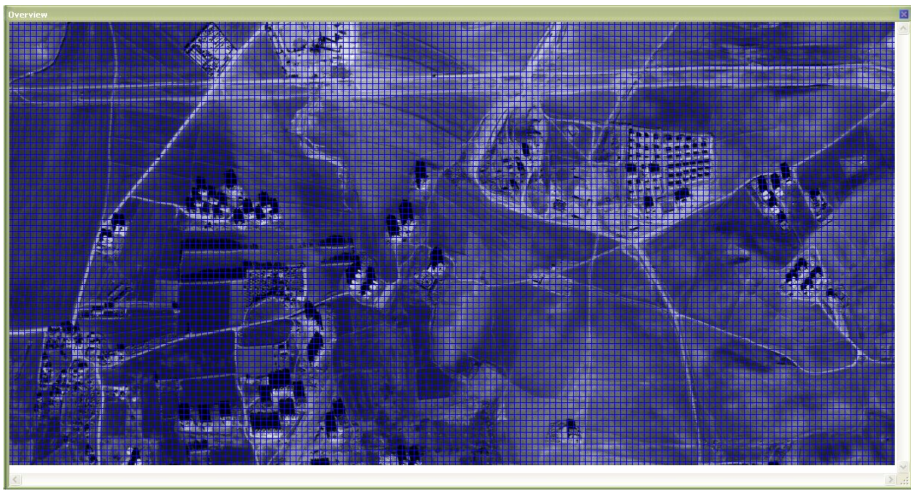


(e) 5th Iteration

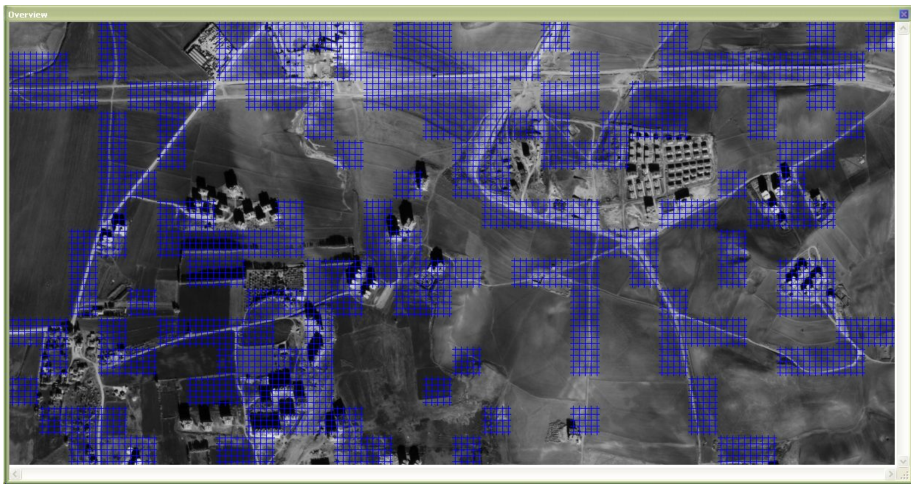


(f) 6th Iteration

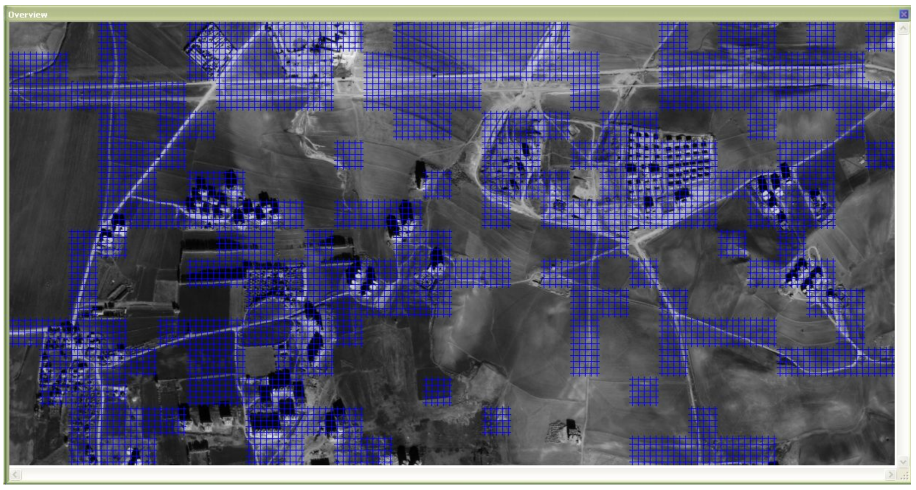
Figure 4.13: Detected targets, training set and ground truth information on experiment image in iterations of the run with SVDD for road experiment (Prototype experiment 2).



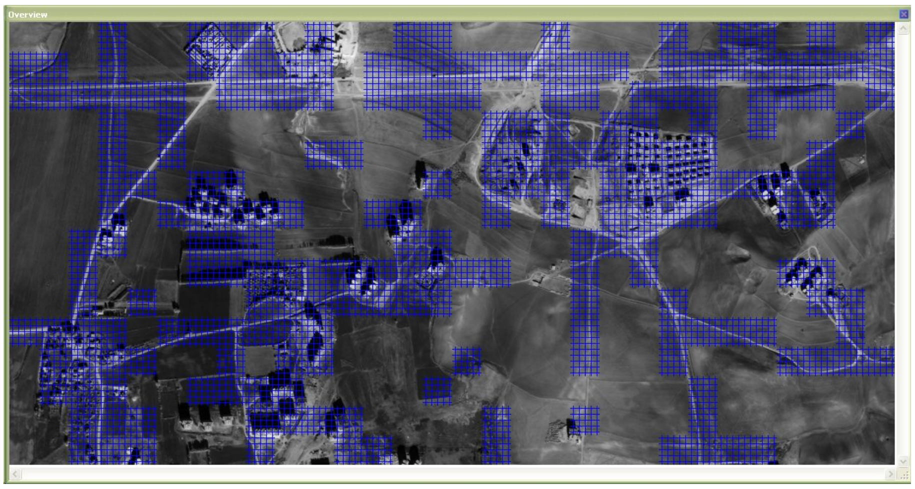
(a) 1st Iteration



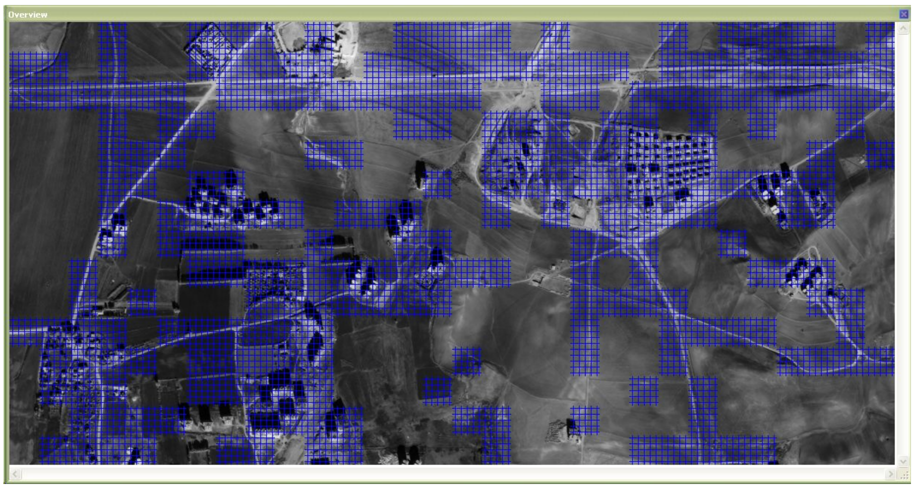
(b) 2nd Iteration



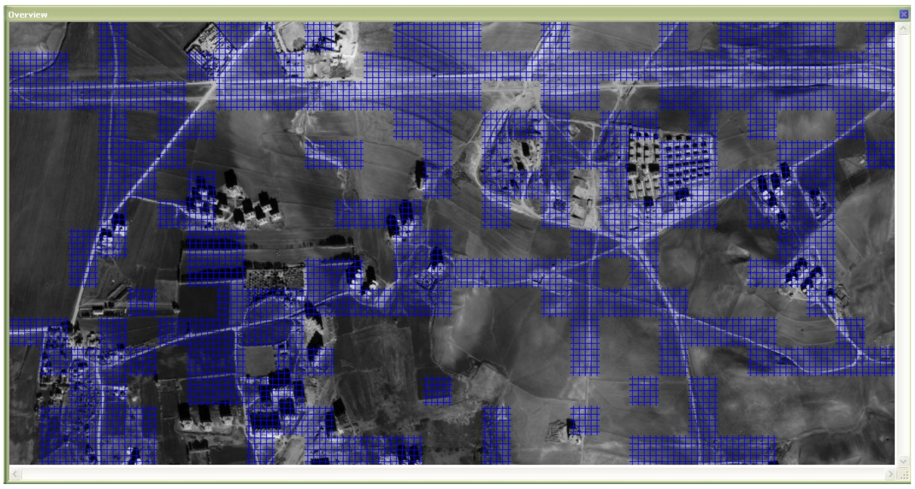
(c) 3rd Iteration



(d) 4^{th} Iteration

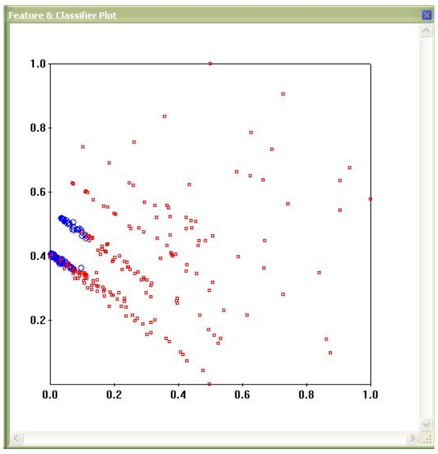


(e) 5^{th} Iteration

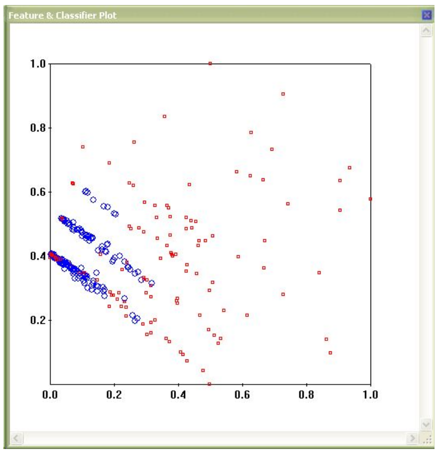


(f) 6^{th} Iteration

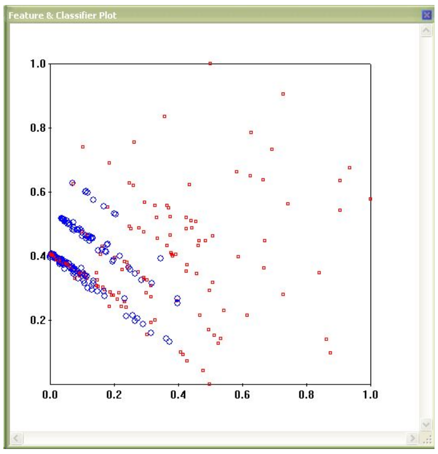
Figure 4.14: Detected targets, training set and ground truth information on experiment image in iterations of the run with SVM for road experiment (Prototype experiment 2).



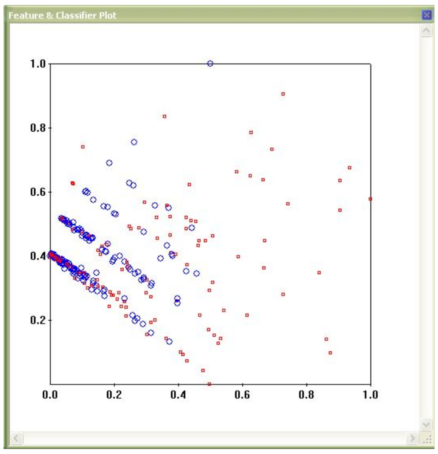
(a) 1st Iteration



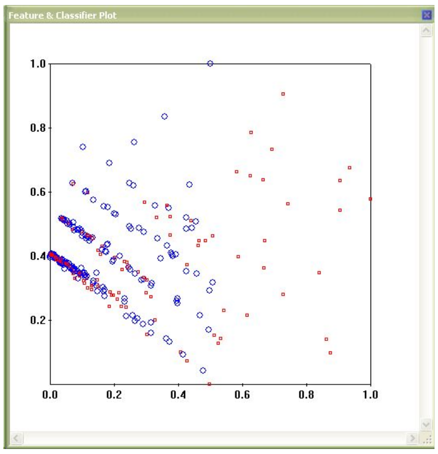
(b) 2nd Iteration



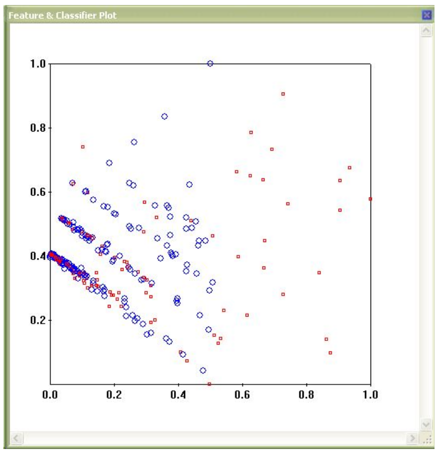
(c) 3rd Iteration



(d) 4th Iteration

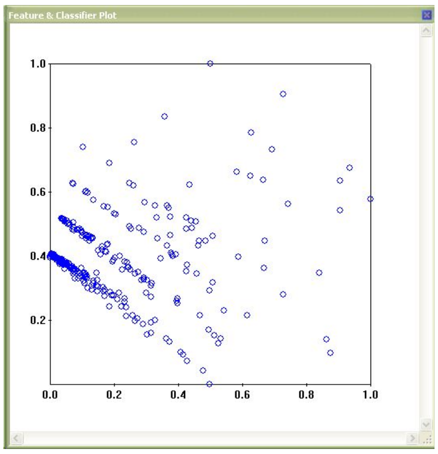


(e) 5th Iteration

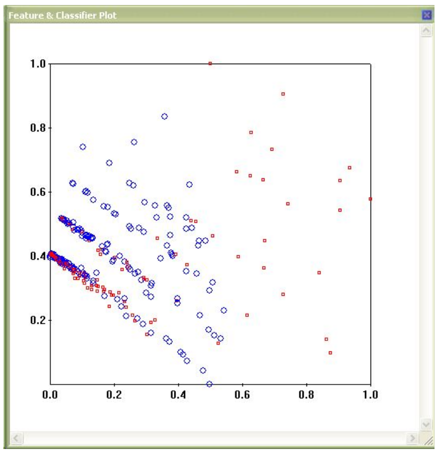


(f) 6th Iteration

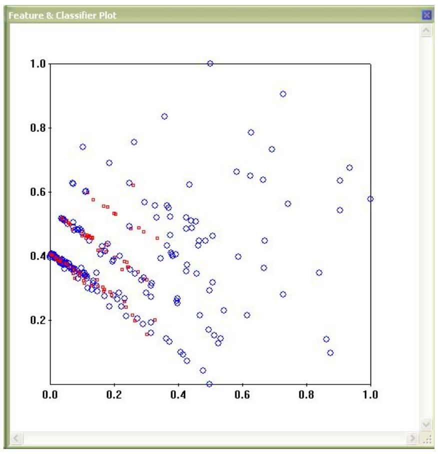
Figure 4.15: Classification results, obtained with SVDD in road experiment (Prototype experiment 2), shown in scaled feature space. Outliers marked with □ and targets with o.



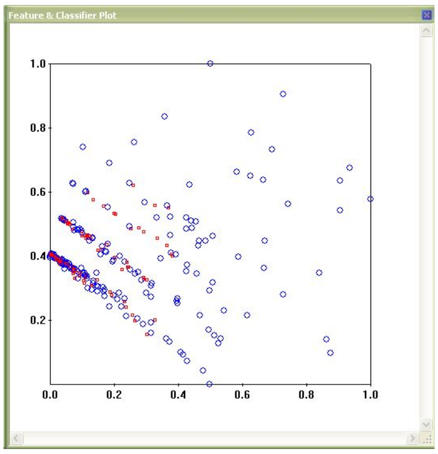
(a) 1st Iteration



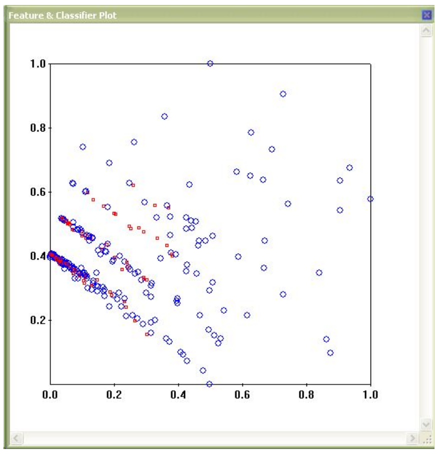
(b) 2nd Iteration



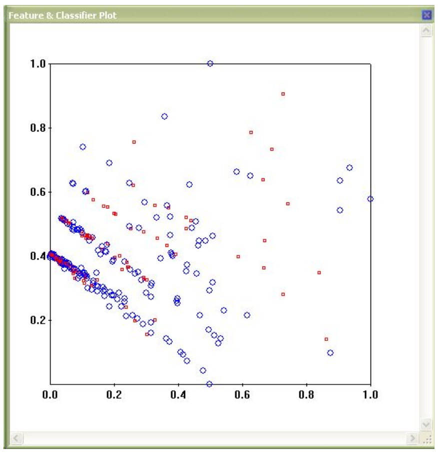
(c) 3rd Iteration



(d) 4th Iteration



(e) 5th Iteration



(f) 6th Iteration

Figure 4.16: Classification results, obtained with SVM in road experiment (Prototype experiment 2), shown in scaled feature space. Outliers marked with □ and targets with o.

4.3 Comments On Experiment Results

In both of the performed experiments, we expect to have a steady improvement on the precision and recall values at each iteration, since the size of the training sets are increasing. In addition, we expect to have better results with SVDD compared to Parzen density estimation and SVM in early iterations, since the latter two classifiers require larger training sets to produce results close to that of produced by SVDD. Also, we expect Parzen density estimation and SVM to produce better recall results when the size of the training sets becomes larger, which occur only in final iterations.

4.3.1 Urban Area Experiment

Performance of SVDD and Parzen density observed in each iteration of the urban area experiment is given in Table 4.6 and Table 4.7, respectively.

In the 1^{st} iteration, since size of the training set is relatively small, number of support vectors, which is inversely proportional to the kernel width, is 3. Kernel width is set to 1 (greater than the maximum distance between targets) and in Figure 4.11a we observe that, SVDD forms a rigid spherical data description, as described in Figure 2.4. Even if the kernel width is greater than the maximum distance between targets, 25% of targets are missed, since SVDD is bounded by the spherical data description around the furthest targets, which are support vectors, in training set. In our initial training set, targets are very close to each other. In addition ,due to small size of the area inside the classifier boundary, a few outliers are detected as targets. The false positives in this iteration is the minimum of false positives in any iteration.

In the 2^{nd} iteration, increase in the number of target objects in the training set causes an increase in true positives but a decrease in true negatives as well, since the target area is considerably larger than that of the 1^{st} iteration. The precision also decreases in parallel to the increase in false positives. However, our aim is to increase the true positive rate in early iterations and tighten the boundary in later ones. 3^{rd} and 4^{th} iterations produce results supporting our expectations. In the 3^{rd} iteration kernel width is set as 0.6 and with the help of the increase in the number of examples, true positives increase. In the 4^{th} iteration kernel width is set as 0.5. The change in kernel width does not result an increase in true positives, but it decreases the number of false positives, which results in a better precision than the previous iteration. In the final iteration, the kernel width is set to 0.51. In all of the iterations target rejection rate is set 0.1, but the number of support vectors increase in parallel with the training set size.

For the second run of the prototype experiment, we use Parzen density estimation with the same data set generated in the first run. The only free parameter, width is set to 0.1 for the first two iterations and 0.15 for the last three iterations. The results for the first four iterations show that, with the increase in the number of targets in the training set, recall increases but precision decreases. This result is mainly due to the spectral features, which can not separate target and outlier objects well enough. In final iteration more outliers are added to the training set, which causes and increase in precision while preserving the recall at %97.

4.3.2 Road Experiment

Performance of SVDD and SVM in each iteration of the road experiment is given in Table 4.8 and Table 4.9, respectively.

In parallel to the results obtained in urban area experiment, the results of the road experiment steadily become better at each iteration. In the 1^{st} iteration, SVDD produces a less precise result compared to the result obtained in urban area experiment with the same size of training set, since the size of the training set required for precise classification becomes larger when the dimension of the features increases, and in this case urban area features are two dimensional while linear features have ten dimensions. In addition, since SVM classifier is a n-class classifier, without any outlier examples SVM is unable to make a classification. In the subsequent iterations, the relation between the results obtained with SVM and the results obtained with SVDD is similar to the relation between results obtained by SVDD and Parzen density estimation in urban area experiment. In order to achieve precision values close to SVDD classifier, both Parzen density estimation and SVM requires larger number of examples, which occur only in final iterations.

Results obtained from the runs support our combined approach, since it can be easily observed that Parzen density estimation produces less precise results than SVDD classifier and within a loose boundary it is more difficult for user to identify the crucial objects that lie aside the boundary. Therefore starting the iterations with SVDD classifier enables the user to steadily increase recall without loss of precision. In the final iterations, with a large number of training set, maximum recall is obtained by Parzen density estimation with a slight decrease in precision. The increase in precision in the final iteration of run with Parzen density estimation is due to the increase in outlier examples in training set. At the end of the iterative classification process, the aim is to reduce the number of objects required to be further classified by different methods (model based etc.), with preserving almost all of the targets in the original image.

4.4 Comparison With Passive Learning

With our prototype and classification software, we showed that one class classifiers are suitable for active learning systems. However, it is still interesting to compare our approach with passive learning techniques. For this purpose we repeated our road detection experiment with the same size of training sets, used in the last iteration of road detection prototype experiment. This time, there was no interaction between the user and the software and the training set was randomly generated from the labeled road experiment image. SVM classifier is used with the same parameters from the prototype experiment. The results of these ten experiments are given in Table 4.10.

Table 4.10: SVM classifier performance observed with randomly generated training sets.

Test number	True positives	False positives	True negatives	False negatives	Precision	Recall
1	119	135	188	8	0.47	0.94
2	111	130	193	16	0.46	0.87
3	105	116	207	22	0.48	0.83
4	105	145	178	22	0.42	0.83
5	109	124	199	18	0.47	0.86
6	111	145	178	16	0.43	0.87
7	102	104	219	25	0.50	0.80
8	112	139	184	15	0.45	0.88
9	114	156	167	13	0.42	0.90
10	113	158	165	14	0.42	0.89

Results obtained from these experiments showed that, our iterative approach produces better results in both recall and precision (approximately 0.05 better from the average recall of 86.7% and 0.15 better from the average precision of 45.2%). The difference in precision is much larger than the difference in recall. There are two main reasons for this. The number of the outlier examples in the training set is half of the number of target examples. Therefore it is very important to choose outliers near to the boundary around the target class to tighten it and to decrease the number of false positives. In our interactive approach, at each iteration wrongly classified outliers are corrected by the user, forming a tight boundary around the targets despite the imbalance between the number of outlier and target examples. However with randomly generated training set, since the number of outliers (323) in whole image is much larger than the number of targets (127), the possibility of choosing an outlier far from the target boundary is high. These outlier examples far from the target boundary has no or very little effect on the decision performance of the classifier, which causes low precision in results.

Chapter 5

Conclusion

Recent satellites provide panchromatic images with very high spatial resolution. In order to reveal valuable semantic information from these images, remote sensing applications should be employed. In this study, we implement an interactive classification software attempt to detect man made geographical objects in satellite images. An interactive system is chosen because of the following observations:

- With high spatial resolution, even in a single satellite image, the amount of the available data is very high which makes the offline training times very long.
- In our case where classification is performed on visual data, user interaction is very convenient and meaningful for improving the classification algorithm.

In order to prove the concept of our approach, before the design and development of the interactive software system, a Matlab prototype is implemented. Results observed with the prototype, supported our approach and lead us to the development phase of the software.

We have built a software, which provides a classification framework combining

- user interaction,
- spectral and linear feature extraction methods,

- one class classifiers including SVDD and Parzen density estimation,
- binary classifier (SVM),
- and visualization tools for features and classification results.

The major aim of the classification process, is to keep true positives high while reducing the number of false positives. We implemented two different image features (spectral and linear) for detecting man-made structures, such as roads, buildings, bridges and urban areas. In order to guide the user throughout the classification process, we provided some visual tools such as a 2-dimensional plot view. For two dimensional features plot view directly shows the feature vectors for image regions, on the other hand if the dimension of the features is higher than two multidimensional scaling (MDS) is employed for mapping.

From the conducted experiments, we achieved high recall (higher than 90%) values with both of the spectral and linear features while leaving most of the outliers out of the target description. These results were promising for us, since our main aim was to keep true positives high while reducing the number of false positives. In addition, we conducted experiments to test our interactive approach against passive learning methods. In these experiment we achieved 0.15 increase in precision on the average, which encouraged us as well.

As future work, we plan to include other types of image features to employ in refined classification process, which uses the output of current system as input (size of the input set is highly reduced by filtering most of the outliers). We also think that, a better projection method will help the user to visualize in separating the target image regions from outliers, hence increasing the accuracy of the classification.

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