DETECTION AND CLASSIFICATION OF OBJECTS AND TEXTURE

A THESIS

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By

Hakan Tuna

July 2009

I certify that I have read this thesis and that in my opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

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ABSTRACT

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M.S. in Electrical and Electronics Engineering

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July 2009

Object and texture recognition are two important subjects in computer vision. An efficient and fast algorithm to compute a short and efficient feature vector for classification of images is crucial for smart video surveillance systems. In this thesis, feature extraction methods for object and texture classification are investigated, compared and developed.

A method for object classification based on shape characteristics is developed. Object silhouettes are extracted from videos by using the background subtraction method. Contour of the objects are obtained from these silhouettes and this 2-D contour signals are transformed into 1-D signals by using a type of radial transformation. Discrete cosine transformation is used to acquire the frequency characteristics of these signals and a support vector machine (SVM) is employed for classification of objects according to this frequency information. This method is implemented and integrated into a real time system together with object tracking.

For texture recognition problem, we defined a new computationally efficient operator forming a semigroup on real numbers. The new operator does not require any multiplications. The codifference matrix based on the new operator is defined and an image descriptor using the codifference matrix is developed. Texture recognition and license plate identification examples based on the new descriptor are presented. We compared our method with regular covariance matrix method. Our method has lower computational complexity and it is experimentally shown that it performs as well as the regular covariance method.

Keywords: : Object detection, object classification, texture classification, codifference matrix

ÖZET

OBJE VE DOKU TESPITI VE SINIFLANDIRMASI

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Elektrik ve Elektronik Mühendisliği Bölümü Yüksek Lisans
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Obje ve doku tanımlaması bilgisayar görüşü konusundaki iki önemli konudur. Resimleri sınıflandırmak için, kısa ve etkili bir nitelik vektörünü hesaplayacak yine hızlı ve etkili bir algoritma, video gözetim sistemleri için kritik bir önem taşır. Bu tezde obje ve doku sınıflandırması için nitelik çıkarma metodları incelemesi, karşılaştırması ve geliştirilmesi yapıldı.

Şekil karakteristiğine dayalı bir obje sınıflandırma sistemi geliştirildi. Arkaplan çıkarımı tekniği ile obje silüetleri çıkarıldı. Bu silüetlerden objelerin çevreleri elde edildi ve bu iki boyutlu sinyal bilgisi, bir tür dairesel dönüşüm ile tek boyutlu sinyal bilgisine dönüştürüldü. Ayrık kosinüs dönüşümü kullanılarak bu tek boyutlu sinyallerin frekans bilgisi elde edildi ve bu frekans bilgisi ile destekçi vektör makineleri kullanılarak sınıflandırmaya sokuldu. Bu metod uygulamaya geçirildi ve obje takibi yapan gerçek zamanlı bir sisteme entegre edildi.

Doku tanımlaması için, reel sayılarda verimli hesap yükü olan ve yarı grup tanımlamasına giren yeni bir işlem tanımlandı. Yeni işlem çarpma işlemine ihtiyaç duymamakta. Bu yeni işleme dayalı bir ortak fark matrisi tanımlandı, ve bu ortak fark matrisine dayanan bir görüntü tanımlayıcı geliştirildi. Bu yeni görüntü tanımlayıcıya dayanan doku tanımlama ve araç plakası tespit örnekleri sunuldu. Yeni geliştirilen bu metod, ortak değişinti matrisi ile karşılaştıldı. Kendi metodumuzun daha az karmaşık hesap ihtiyacına rağmen ortak değişinti matrisi ile benzer sonuçlar verdiği deneysel olarak gösterildi.

Anahtar Kelimeler: Obje tespiti, obje sınıflandırması, doku sınıflandırması, ortak fark matrisi

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Dedicated to my family . . .

Chapter 1

INTRODUCTION

1.1 Overview

Video surveillance systems are getting more popular every day in monitoring security sensitive areas such as banks, highways, borders, forests etc. In general, video outputs of the more sensitive areas are processed online by human operators and the remaining video outputs are recorded for future use in case of a forensic event. However, as the number of surveillance systems increase, human operators and storage devices are becoming insufficient for operating of these systems. As the surveillance systems migrate from analog to digital systems, and increase in numbers, a need for automatically interpreting the captured video arises. Increasing computational power and advances in camera systems give rise to computer aided smart video systems. Our motivation is, a computer aided video surveillance system can decrease the need for human interaction. These systems must be robust, efficient and fast in order to process real time videos.

In this research, we investigated two major subjects in computer vision. We developed and introduced new feature extraction and classification methods for object and texture recognition systems. Both methods have low computational costs, thus they are appropriate for real-time applications.

In the first part of the thesis, we introduce a system for automatically detecting and recognition of objects in video. By using a background model, any objects entering the scene are detected and classified. The system can be used by both grayscale and color cameras and robust to illumination changes and scale. This system is integrated and operated on a real-time video system.

The second part of the thesis covers the texture recognition problem which is another important subject in computer vision. We propose a new method for texture recognition problem by modifying a previous approach, covariance matrix. Covariance matrix method is lately presented by Porikli and is shown to outperform other methods in texture retrieval processes. However, for scanning large images and real time applications computational cost of covariance matrix can grow dramatically. In order to decrease the computational cost of the process, we modified the covariance equation and developed the codifference matrix method. We tested the performance of the proposed texture recognition system using the brodatz texture database and two license plate databases. Proposed method gives very good results similar to the original method in texture recognition experiments with a lower computational complexity and can be used as an alternative to the original method where computational cost is an important constraint.

1.2 Organization of the thesis

Organization of the thesis is as follows. In Chapter 2, we survey the previous approaches to object and texture recognition problems. In Chapter 3, we explain the proposed method for object detection and classification, and in Chapter 4, we explain our feature extraction method for texture recognition problem. Finally, Chapter 5 includes the conclusions about the thesis.

Chapter 2

RELATED WORK

2.1 Object Detection and Classification

There are many object recognition techniques proposed earlier [1-7]. In general, 2-D object recognition techniques can be classified in two major categories as statistical methods and syntactic methods. In statistical methods, a set of measurable features are extracted from the object images and the images are represented in an n-dimensional feature space. If the features extracted from image classes are distinctive, feature space is well clustered. Syntactic methods describes a set of rules in order to represent structural information of the images. It has advantages in describing highly structured and complex patterns when statistical approaches are not sufficient. Statistical and syntactic methods have advantages and disadvantages over each other, and combination of these two approaches into an adaptive system is possible.

Belongie and Malik used shape context for shape matching [1]. They represent shapes by a discrete set of points sampled from the internal or external contours of the objects. Shape contexts use the relative distribution of these points. The position information of every other point relative to a chosen point are calculated in log-polar coordinates. Number of points are counted for different bins of r and ϕ values and this way a histogram information is extracted for every point. However, different reference points give completely different shape contexts so shape contexts with reference to every point in the shape must be calculated. This system is appropriate for template matching algorithms but they do not extract characteristic information of shapes.

Curves and skeletons are also used as shape descriptors. Curves do not give information about the interior of the objects, however they are used in so many applications effectively [2],[3]. Outline curves are used for object description with their curvature, bending angle and orientation properties. Skeletonizing, on the other hand, gives information about both the interior and outline of the shape, and also widely used [4],[5]. Sebastian and Kimia have a good comparison of these two shape descriptors in the literature [6]. Skeletons have a better performance in shape retrieval experiments than the curves, together with a drawback on the computational cost.

Serre and Pogio simulated human visualization by using a multilayer neural network [7]. Image scenes are filtered with a set of gabor filters, local maximas of filter responses are used as feature sets. Of course these are very computationally heavy operations which are not appropriate for real-time applications.

2.2 Texture Detection and Classification

Texture recognition and classification is a widely studied subject in computer vision. There are several well documented studies in the literature. Most of the works have focused on finding good features for texture retrieval process.

Haralick proposed co-occurrence matrix, which is also referred to as a co-occurrence distribution [8]. In this method, distribution of co-occurring values in an image at a given offset are calculated in order to form a co-occurrence matrix, and several features are extracted from this matrix for texture recognition task. Co-occurrence matrix is sensitive to spatial frequencies of the texture, however it is not recommended for textures with large primitives.

Statistical features of textures are also used for classification. Antoniades and Nandi used second and third order statistics directly for differentiate texture images [9]. The classification ability of the system is very primitive and can not be used to differentiate a large database of texture images.

Gabor filtering is another widely used approach in texture recognition [10],[11],[12]. Qaiser et.al fuses gabor and moment energy features of textures for a better texture recognition [13]. Fusing two different approaches gives better results than individual ones.

Lin, Wang and Yang adopt a structural approach for texture retrival from an image database, rather than using frequency domain methods [14]

There are several feature extraction techniques for texture categorization, recognition and classification tasks. Ma and Zhang has a well prepared survey about different feature extraction methods for image retrieval and comparison of their performances [15].

Recently, Porikli and et.al. introduced covariance matrix as a new region descriptor for texture recognition task [16]. Covariance matrix is shown to outperform previous feature extraction methods in several texture retrieval and classification experiments.

Chapter 3

OBJECT DETECTION AND CLASSIFICATION

Object detection and classification system is composed of an object detection system based on background subtraction method and a classification system based on shape features. So it has both advantages and disadvantages of these systems.

The system comprises of three main steps

1. Object detection
2. Feature extraction
3. Object classification

First step includes detection of the pixels that the object lays on. We use background subtraction method for discriminating the background pixels from the foreground pixels which contains the objects of interest. This way, any new object entering the scene is detected by using the difference image between the background model and the current frame. From the difference image, object shapes are obtained.

In the second step, we use the boundaries of the objects for feature extraction. We extract the contour points from the black and white silhouettes, take the modified radial function (MRF) of these contour signals and transform these signals into the frequency domain. We investigate DCT (Discrete Cosine Transform), DFT (Discrete Fourier Transform) and Wavelet Transformation of these signals and use the coefficients of these transformations in classification step.

Third step includes the classification of objects by using these features. This step employs an SVM(support vector machine) algorithm. Each transformation is experimented and success rates are compared.

3.1 Object Detection

The first step of the program is to detect the regions where object occupies in the image and extract the shape information of these objects. We used background subtraction method in order to distinguish the object from the background image. After using morphological operations and noise removal, blob of the object silhouette is extracted from the image by using connected component analysis.

3.1.1 Background Subtraction

Background subtraction is a widely used method for discriminating the background from the objects of interest [17]. Foreground pixels are basically detected by subtracting the current frame pixel-by-pixel from a background model. The pixels with a difference higher than a threshold value is classified as foreground pixels; and the pixels with a difference lower than this threshold value is classified as background pixels. Figure 3.1 depicts a sample background subtraction operation.

Background subtraction is known to perform well in static backgrounds. It is very sensitive to the changes in the illumination. However, in order to overcome this situation and decrease the sensitivity of method for illumination changes, background model can be updated with every new frame.

A pixel in the current frame at location (x, y) and at time t is denoted by $I_t(x, y)$, and the pixel in the background model updated at time t, at location (x, y) is denoted as $B_t(x, y)$.So, $I_t(x, y)$ is considered as a foreground pixel if

$$|I_t(x, y) - B_t(x, y)| \geq \tau \tag{3.1}$$

where τ is a pre defined threshold. We use pixels below this predefined threshold in the background update. This way, foreground pixels in which detected object lays on do not effect the background model. Background model is updated with the following function.

$$B_{t+1} = \alpha I_t + (1 - \alpha)B_t \tag{3.2}$$

Selection of these parameters has a significant effect on the performance of the system. High threshold values cause misdetection of the objects in the scene, or cavities in the object silhouette. On the other hand, lower threshold values cause a noisy output. Background model update also should be handled carefully. If the update parameter α is too high, objects in the scene may corrupt the background model, while if it is too low, system becomes too sensitive to illumination changes in the scene.

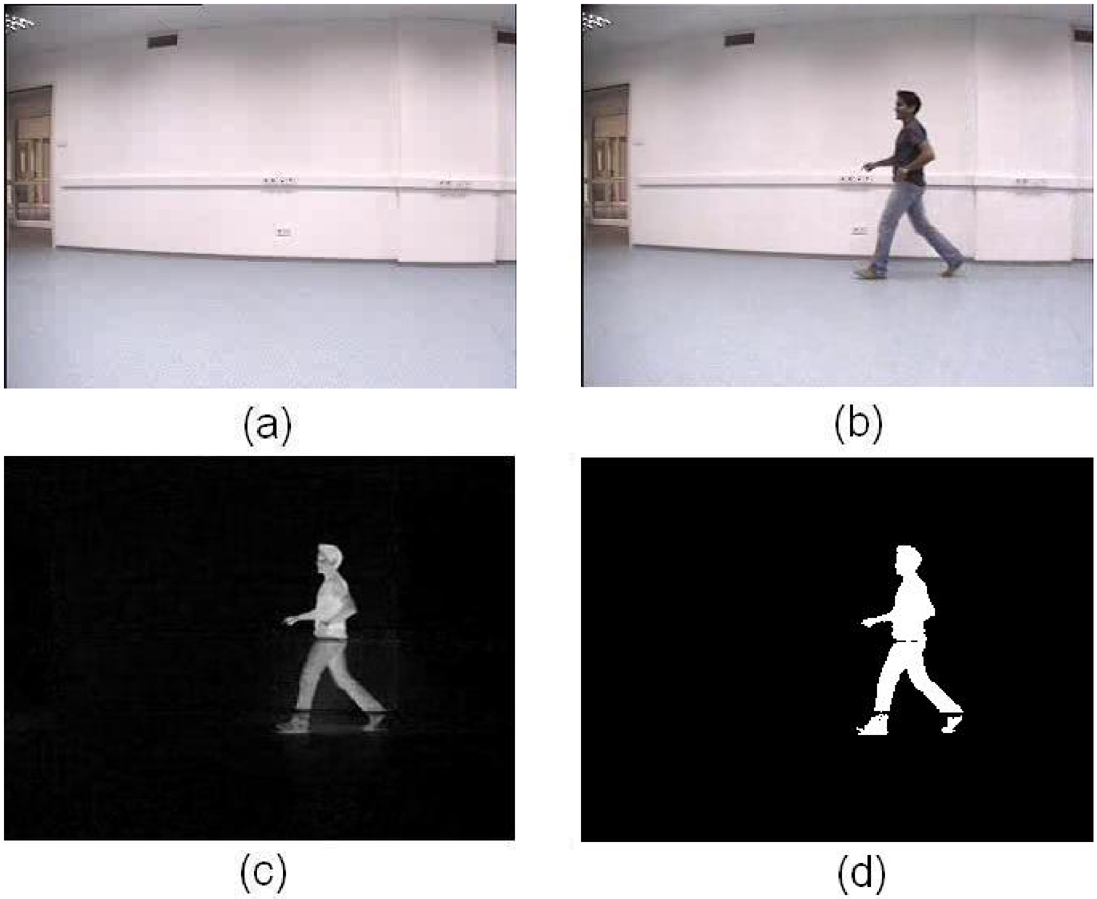


Figure 3.1: Background Subtraction; a)Background Model b)Current Frame c)Difference Function d)Thresholded difference function

3.1.2 Image Enhancement

The difference function between the current frame and the background model is not sufficient to extract the silhouettes of the objects. Noises in the difference image caused by camera noise or changes in the ilumination must be handled accordingly. Also similarities between the background model and the object texture may cause some occlusions on the image silhouette.

The first step for removing nosie in the image is to apply a threshold value. Thus, before proceeding, difference image is thresholded by a constant value and transformed to a binary image. This threshold value is determined manually according to the response of the difference image. If this threshold value is low, then we obtain an image with a high level of noise. On the other hand, if this threshold value is chosen to be high, then some occlusions or holes can occur in the image. This second condition is very crucial because object silhouettes can split into two or more parts which will totally change the shape information. Therefore we limit the threshold value where occlusions are pretty small with respect to the object silhouette and deal with noise in the background pixels in further steps.

After using a threshold value, we obtain a binary image with black (background pixel) and white (foreground pixel) pixels. We use morphological operations in order to remove noise and holes in the image. (erode, dilate, opening, closing). Opening removes small noises from the background image and closing removes small occlusions in the foreground image.

We use connected component analysis in order to obtain object silhouettes in the image. Very small components are neglected as a last noise removal step and objects big enough are saved for further processing.

Figure 3.2 shows the difference image and the resultant image after image enhancement operations.

3.2 Feature Extraction

In this step we start with black and white silhouettes of the detected objects. From the black and white silhouettes, the contour points of the objects are extracted. We take the modified radial transformation of these contour points and then transform the obtained signal to the frequency domain.

Figure 3.2: a)Object silhouette obtained from background subtraction b)Object silhouette after image enhancement operations

3.2.1 Modified Radial Transformation

The rectangular coordinates of contour points obtained from the contour extraction step are not suitable for representation of object shapes, because this coordinate representation is not invariant to rotation and scale. Also, because 2-D contour information is hard to employ, we should reduce the dimension of contour information. An alternative method for this is to use radial transformation. This transformation uses the idea that, every point on the boundary can be approximated as a vector projected between a reference point and the point on the boundary. Thus, the points on the boundary of an object are represented with r and ϕ values instead of x and y, where r corresponds to the distance between the reference and the boundary point, and ϕ coresponds to the angle between the radial vector and a reference axis. If we increase ϕ with equal angles and record $r(\phi)$, we obtain a 1 dimensional signal which also has the rotation invariance property. This representation has been used in many applications [18],[19].

However, radial transformation outputs multiple values when the radial vectors intersects the boundary more than once. In these cases, radial function must be modified or must be handled carefully in order to represent object contours. In order to overcome this situation, we use modified radial function (MRF) which was proposed earlier in [20].

In modified radial function, we do not take the angularly equispaced points on the contour, instead we move on the contour arc with equal distance values and project the vector from the reference point to these points on the boundary. This way, modified radial function (MRF) represents the distance and angle components with respect to another parameter l, where l corresponds to the arc length from a reference starting point to the point on the boundary. In this transformation, we both have a distance component $r(l)$ and angle component $\phi(l)$ for a full representation of the contour points. However, in our method we do not take the angle component $\phi(l)$ and continue only with the distance component $r(l)$.

We generally set the starting point on the boundary as the top left corner of the contour and the reference point as the centroid of the object contour. Since the increments of l are not usually equally-spaced, we used linear interpolation to take exactly 64 samples from every contour.

In order to gain scale robustness, we scale the data such that the area under the graph is always constant. Therefore we end up with a normalized 64-point data signal. The MRF of the silhouette obtained in object detection step is depicted in figure 3.3.

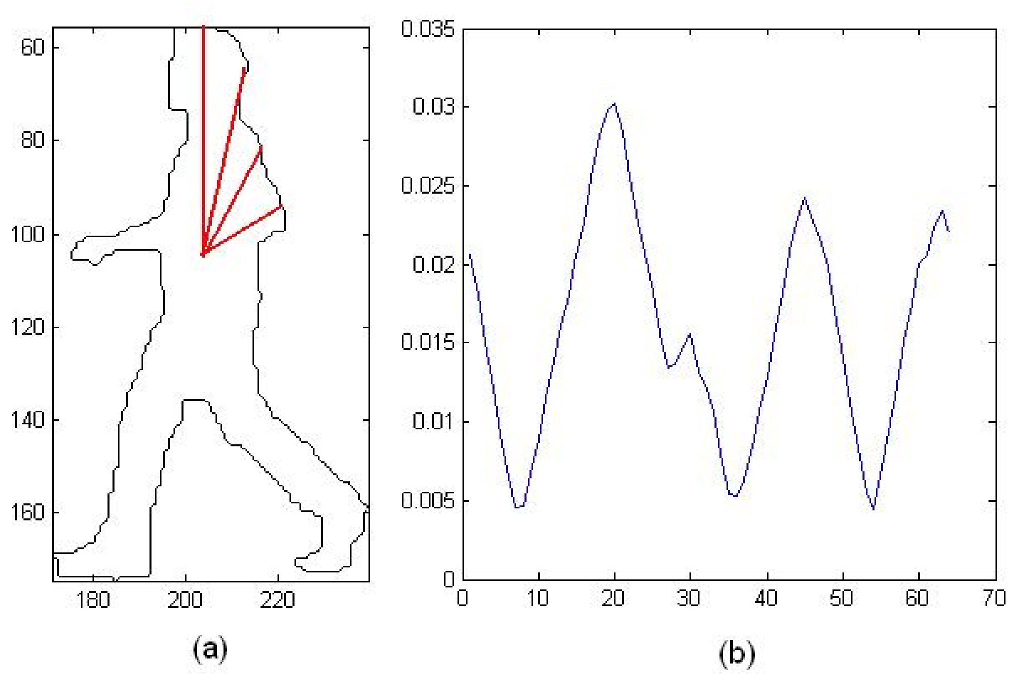


Figure 3.3: Modified radial transformation. (a) Contour of the silhouette in fig. 3-1d, (b) corresponding 1D radial transformation

3.2.2 Discrete Cosine Transformation

Discrete Cosine Transform (DCT) is a linear, invertible transformation which expresses discrete signals in terms of a sum of cosines with different amplitudes and frequencies. Discrete cosine transformation is conceptually very similar to Discrete Fourier Transformation (DFT). However it uses only real coefficients on the contrary to Fourier transform, which uses complex coefficients.

The mathematical formula for discrete cosine transformation is

$$y(k) = w(k) \sum_{n=1}^{N} x(n) cos \frac{\pi(2n-1)(k-1)}{2N}, k = 1, ..., N \tag{3.3}$$

where

$$w(k) = \left\{ \begin{array}{l} \frac{1}{\sqrt{N}}, k = 1 \\ \frac{2}{\sqrt{N}}, 2 \leq k \leq N \end{array} \right\} \quad (3.4)$$

DCT has a strong energy compaction property, i.e. it does a better job in concentrating the energy in the lower order coefficients [21]. Thus, it has a very wide usage in data compression of image and audio.

We used DCT in order to extract the frequency information of the contour signals. Figure 3.4 shows the DCT of a contour signal. The characteristic features of contour signals are mainly compensated in the lower frequency bands. Therefore we took first 10 coefficients (except the very first one, which corresponds to DC component of the signal and always constant because of the normalization) as the feature vector for each shape.

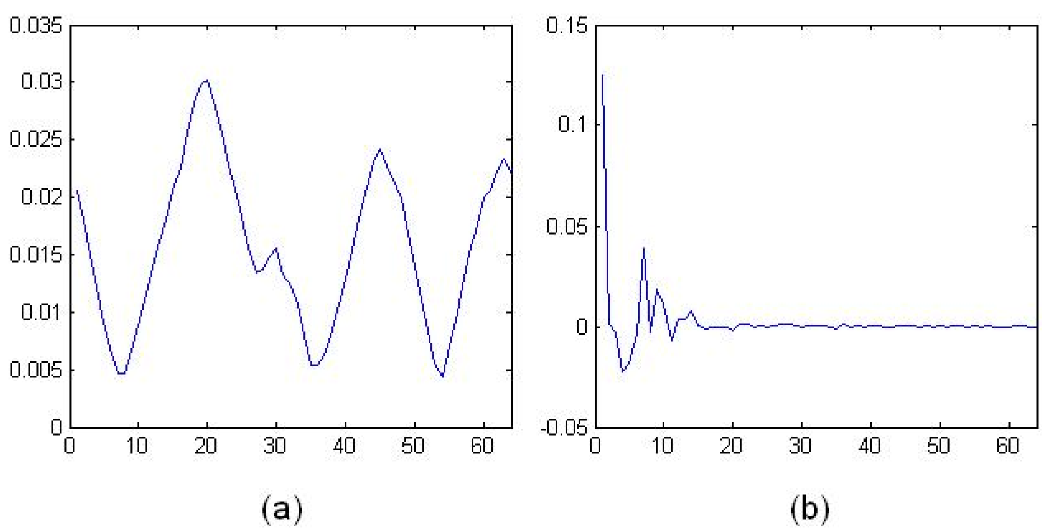


Figure 3.4: a) Contour signal b) DCT tansformation of a

We compared DCT with DFT and wavelet decomposition. We took the 10 coefficients from the same frequency bands for each method. We used Haar wavelet for wavelet decomposition.

Figure 3.5 shows the results of our comparisons. We used three different object classes as human, human group and vehicle. Train set consists of 57 human, 58 human group and 38 vehicle pictures. Test set consists of 56, 64 and 35 images for human, human group and vehicle object groups respectively.

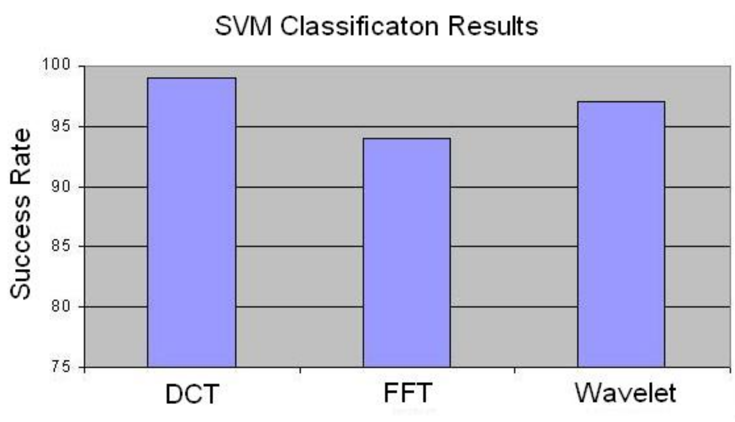


Figure 3.5: Comparison of DCT, DFT and Wavelet decomposition in classification by SVM

3.3 Object Classification

Object classification step is done by a support vector machine (SVM) algorithm.

3.3.1 Support Vector Machines

Support Vector Machines (SVMs) are a type of linear classifiers. SVM uses supervised learning methods, and can be used for both classification and regression. Suppose we have two class input data in an N dimensional feature space. Support vector machines try to find an $N-1$ dimensional hyperplane which divides the space into two and separates these two groups from each other. However, there are probably lots of hyperplanes which splits these two groups. Thus, additionally, support vector machines try to find the hyperplane such that the distance from the closest points from each class to this hyperplane is at maximum. This hyperplane is called the maximum margin hyperplane. Figure 3.3.1 displays these hyperplanes.

We used libsvm library which is widely known and used in classification tasks [22]. We used one model for three classes with RBF(radial basis function) kernel.

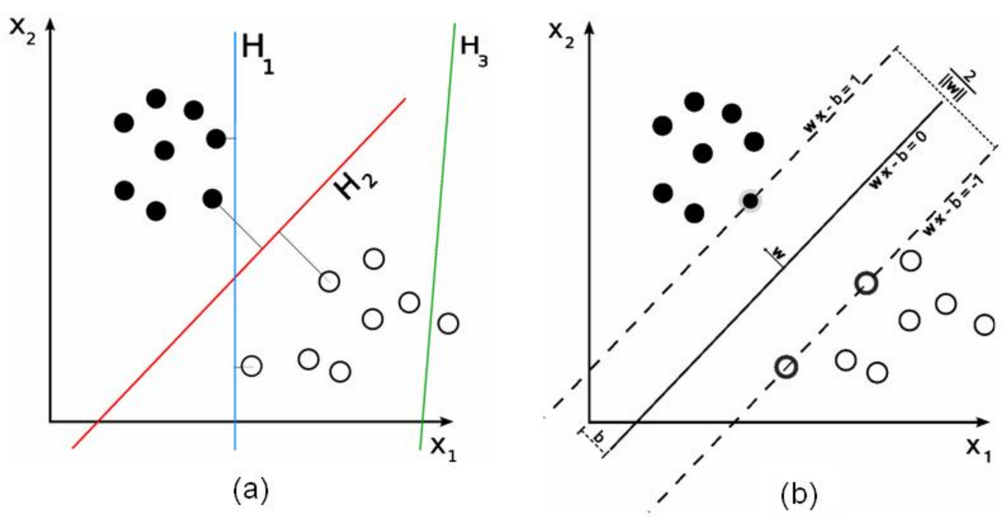


Figure 3.6: SVM classification a) Both H1 and H2 splits two groups, H3 does not. However, H2 has the maximum margin b) Finding the maximum margin. (Images are taken from wikipedia.org internet site)

3.4 Real-Time object detection, tracking and classification system

We integrated our object classification system with a real-time object detection and tracking system [23].

We used three object categories, human, human group and vehicle. Our method showed very good performance in classification of different objects. Errors occur generally because of the improper silhouette extraction in the background subtraction step.

Results of the background subtraction method has a crucial importance in the results of the overall system. Even we achieve to obtain very good results in our experiments, improperly extracted object silhouettes sometimes may corrupt the results. In order to obtain a better classification, we added simple rules into the classification step of the final system.

First, human classes generally have the lowest values of aspect ratio because of their shapes. So we used a threshold value on the aspect ratio of the detected objects. If the detected object has a lower aspect ratio than this threshold, we decided that this object is a human.

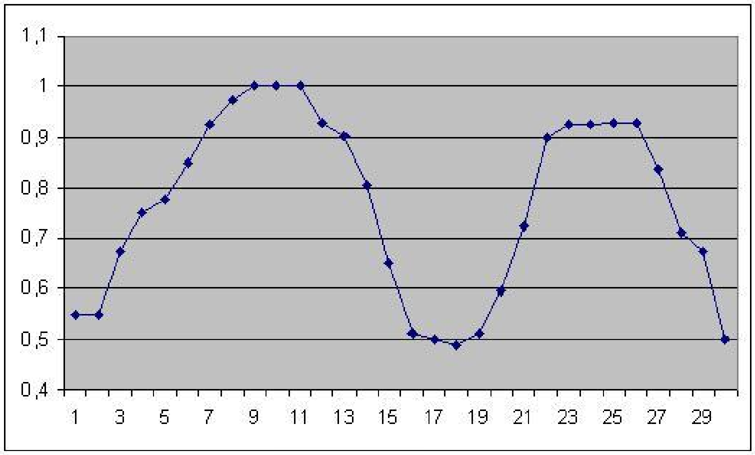
Aspect ratios of bounding rectangles of walking human silhouettes compose a periodical signal, which is very distinctive from other object classes. We recorded the aspect ratio history of detected objects and found the periodicity by using autocorrelation of the signals (Figure 3.7).

$$X(i) = \sum_{n=0}^{N}(x(n) - \mu_x)(x(mod(n-i, N)) - \mu_x) \tag{3.5}$$

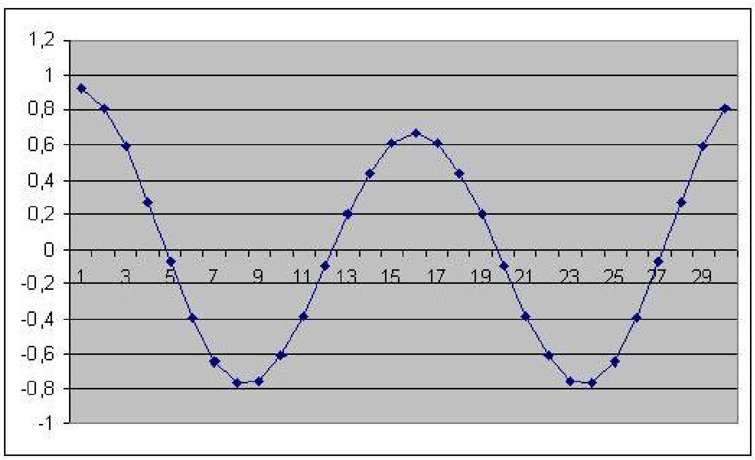
where

$$\mu_x = \frac{1}{N}\sum_{n=0}^{N} x(n) \tag{3.6}$$

In our experiments, we saw that walking human signals produce aspect ratio signals with periodicity with 0.8-1.2 seconds. So, if the detected object is moving and if we find peaks in the autocorrelation function in this range with a value above a certain threshold, system decides that the detected object is indeed a human. Human group and vehicle classes do not produce a periodical signal, instead they produce a chaotic behavior.



(a)



(b)

Figure 3.7: a)Aspect ratio history of the bounding rectangle of a walking human (15 frames per second), b)Circular autocorrelation of the aspect ratio history signal

If the detected object passes these simple classification rules, SVM is employed for classification task.

We also used temporal information of the detected objects in classification. By using tracking system, we recorded the previous results of object detection.

If the detected object does not collide with or detach from another object, we use the previous results of object detection together with the last result to vote for object class. Basically, we used results from 2 previous frames and the current frame. If the previous 2 results agrees with each other but do not agree with the current result, we output the most voted result.

Figure 3.8: Sample screenshots from real-time object tracking and classification system.

Chapter 4

TEXTURE RECOGNITION

Texture is one of the main characteristics for analysis of images, and texture recognition is a very important subject in computer vision. A fast and efficient algorithm for texture description is a vital issue.

We present a new method for texture recognition problem by modifying a previous approach, covariance matrix, and decreasing the computational cost. We call it as codifference matrix. In this proposed method, the multiplication operation of the well-known covariance method is replaced by a new operator. The new operator does not require any multiplications. Codifference matrix method is shown to perform as well as the original previous method, and even outperform the previous one in some tests. Texture recognition and license plate identification examples are presented based on this method.

4.1 Covariance Matrix as a Region Descriptor

Porikli et.al introduced the covariance matrix method as a new image region descriptor, and showed that covariance matrix method performed better than the previous approaches to the texture recognition problem [16, 24]. They also developed an object tracking method using the covariance matrix [25].

4.1.1 Covariance Matrix

Covariance is the measure of how two variables behave according to each other. If the variables tend to vary together, (if one of them is above its expected value when the other one is also above its expected value), the covariance is positive, the covariance is negative if the variables tend to vary inversely (one of them is above its expected value while the other one is below its expected value). The mathematical expression of covariance is as follows

$$cov(a, b) = \sum_{k=1}^{N} (a_k - \mu_a)(b_k - \mu_b) \tag{4.1}$$

If we have n variables α_1, α_2,... α_N, covariance matrix of these variables is defined as

$$C = \begin{bmatrix} cov(\alpha_1, \alpha_1) & cov(\alpha_1, \alpha_2) & \cdots & cov(\alpha_1, \alpha_N) \\ cov(\alpha_2, \alpha_1) & cov(\alpha_2, \alpha_2) & \cdots & cov(\alpha_2, \alpha_N) \\ \vdots & \vdots & \ddots & \vdots \\ cov(\alpha_N, \alpha_1) & cov(\alpha_N, \alpha_2) & \cdots & cov(\alpha_N, \alpha_N) \end{bmatrix} \tag{4.2}$$

Let $\mathbf{f}$ be a d-dimensional feature vector for each pixel $I(x, y)$ of a two-dimensional image.

$$F(x, y) = \phi(I, x, y) \tag{4.3}$$

where ϕ is the feature mapping such as the intensity, gradient or a filter response of the pixel. Let us index the image pixels using a single index k, and assume that there are n pixels in a given image region. As a result we have n d-dimensional feature vectors $(\mathbf{f_k})_{k=1...n}$. The covariance matrix of the image region is defined as

$$C = \frac{1}{n-1} \sum_{k=1}^{n} (f_k - \mu)(f_k - \mu)^T \tag{4.4}$$

where μ is the mean vector of the feature vectors.

For d chosen features, we will obtain a dxd covariance matrix. However, since

$$cov(x, y) = cov(y, x)$$

covariance matrix is symmetric, and since

$$cov(x, x) = var(x)$$

diagonal elements of the covariance matrix are actually variances of chosen features in the region. Thus, for n different features, we will have $n(n+1)/2$ different values in the covariance matrix for computation.

4.2 Codifference Matrix

Computational cost of a single covariance matrix for a given image region is not heavy. However, computational cost becomes important when we want to scan a large image at different scales and all locations to detect a specific object. Furthermore, many video processing applications require real-time solutions. In order to decrease the computational cost, we modified the core function of covariance equation (equation 4.5) and obtained codifference equation (equation 4.6)

$$C(a,b) = \frac{1}{n-1}\sum_{k=1}^{n}(a-\mu_a)(b-\mu_b) \tag{4.5}$$

$$S(a,b) = \frac{1}{n-1}\sum_{k=1}^{n}(a-\mu_a)\odot(b-\mu_b) \tag{4.6}$$

where the operator $\odot$ acts like a matrix multiplication operator, however, the scalar multiplication is replaced by an additive operator $\oplus$. The operator $\oplus$ is basically an addition operation but the sign of the result behaves like the multiplication operation:

$$a \oplus b = \begin{cases} a+b, & \text{if } \ a \geq 0 \ \text{ and } \ b \geq 0 \\ a-b, & \text{if } \ a \leq 0 \ \text{ and } \ b \geq 0 \\ -a+b, & \text{if } \ a \geq 0 \ \text{ and } \ b \leq 0 \\ -a-b, & \text{if } \ a \leq 0 \ \text{ and } \ b \leq 0 \end{cases} \tag{4.7}$$

for real numbers a and b. We can also express Equation 4.7 as follows

$$a \oplus b = \text{sign}\,(a \times b)\,(|a| + |b|) \tag{4.8}$$

or in a more straigtforward mathematical expression

$$a \oplus b = \frac{a \cdot b}{|a| \cdot |b|} (|a| + |b|) \tag{4.9}$$

Our codifference equation behaves similar to original covariance function. If the variables tend to vary together, codifference equation gives positive results as the original equation, if variables tend to vary inversely, codifference equation gives negative results as the original equation. Also since $S(x, y) = S(y, x)$, codifference matrix is symmetric as covariance matrix. On the other hand, computational cost is decreased by replacing the multiplication operation with addition operation.

Operator $\oplus$ satisfies totaliy, associativity and identity properties i.e. it is a monoid function. In other words it is a semigroup with identity property.

4.3 Texture Classification

We use well known Brodatz texture database for texture classification tests. We repeat the same steps with the method described in [16], however we use codifference matrix as a region descriptor instead of covariance matrix, and compare the results of two different image description methods. The classification procedure we followed in these experiments is not computationally efficient, however these texture classification experiments give a good comparison on a well known database between the original and the modified methods.

The Brodatz texture database which we used in our experiments consists of 111 texture images. The size of each image is 640 x 640. Classification is a challenging task because of the non homogeneous texture images in the database. Sample images from Brodatz texture database is shown in figure 4.1. In our experiments, we divide each texture image into 320 x 320 sized four sub-images. Two of these images are used for training and the remaining two are used for testing.

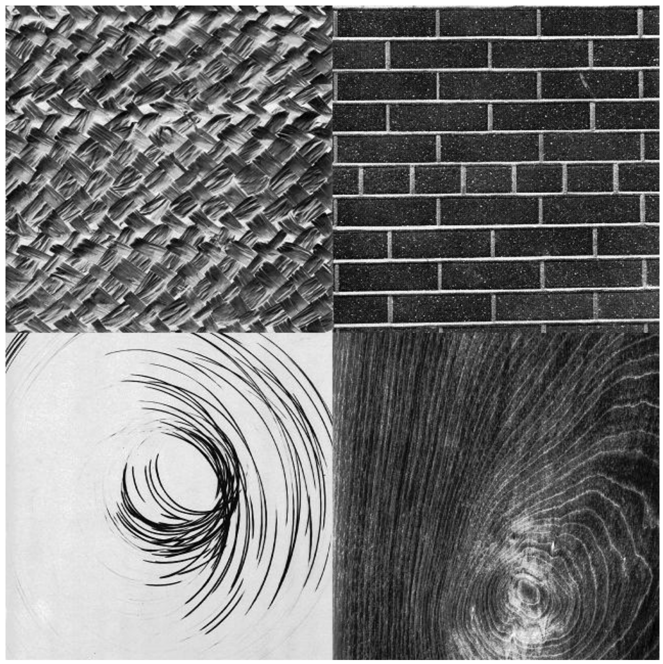


Figure 4.1: Sample images from Brodatz texture database. This database contains non-homogeneus textures as well as homogeneus textures

4.3.1 Covariance Features

In texture classification step, we use 5 different features extracted from texture images. These are intensity values of pixels and the norms of first and second order derivatives of intensity values of pixels in both x and y directions. Feature vector is defined as

$$F = [|I|\,|I_x|\,|I_y|\,|I_{xx}|\,|I_{yy}|] \tag{4.10}$$

Therefore every pixel in a given image region is mapped to a $d = 5$-dimensional feature vector. Then the covariance and the codifference of these features are calculated using both Eq. (4.5) and Eq. (4.6), respectively. As a result, we end up with 5x5 dimensional covariance and codifference matrices, representing each region.

4.3.2 Random Covariance(Codifference) method

For representation of each texture image, we choose 100 regions from random locations in the image. Each region is a square box with random sizes which varies from 16x16 to 128x128. We calculate the covariance and the codifference matrices of each region. Thus, every texture subimage is represented with 100 covariance and 100 codifference matrices extracted from random regions of these images. Since we have 2 subimages from the same texture image, we will have 200 covariance and codifference matrices representing each texture. Figure 4.2 depicts the random covariance(codifference) matrix method.

4.3.3 K-nearest neighbor algorithm

For classification task, we employ k-nearest neighbor algorithm.

K-nearest neighbor algorithm (k-NN) is a supervised learning method which classifies samples according to majority of the closest training samples in the feature space.

We use a generalized eigenvalue based distance metric to compare covariance and codifference matrices which was introduced in [26] [27] and used in [16] as a

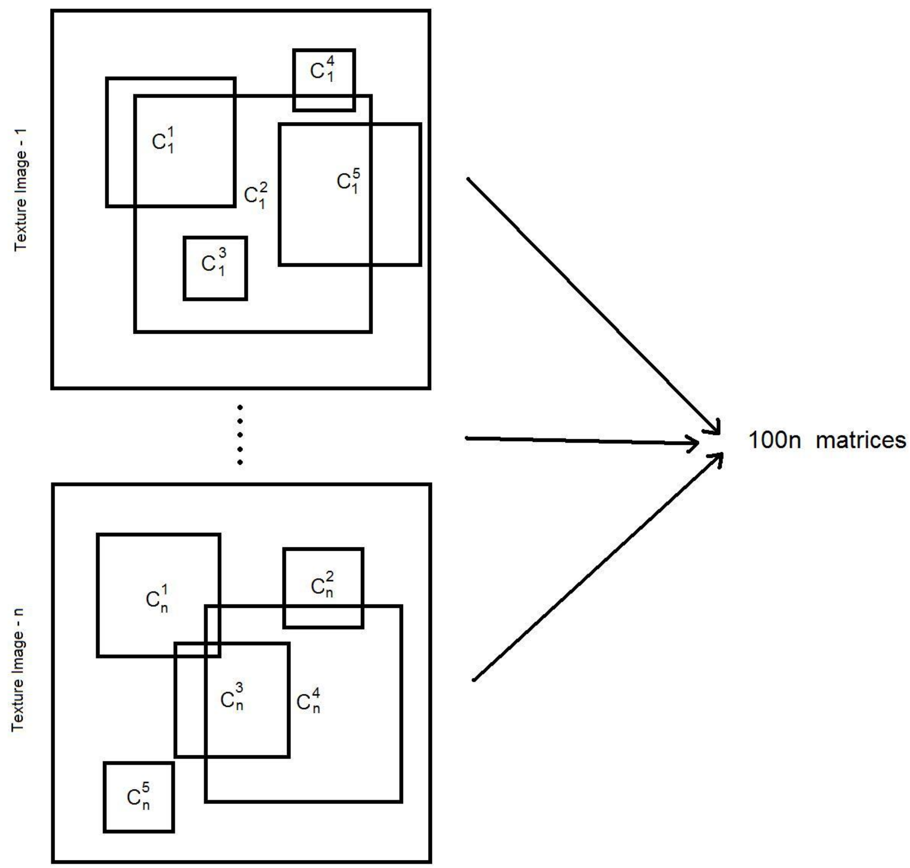


Figure 4.2: Random Covariance (Codifference) Method

part of the k-NN method:

$$d(C_1, C_2) = \sqrt{\sum_{k=1}^{n} ln^2 \lambda_i(C_1, C_2)} \tag{4.11}$$

$\lambda_i(C_1, C_2)$ is the generalized eigenvalues of matrices C_1 and C_2. Distance function is a metric, i.e. it satisfies the following conditions

1. Positivity: $d(A, B) > 0$ and $d(A, B) = 0$ only $if A = B$.

2. Symmetry: $d(A, B) = d(B, A)$.

3. Triangle inequality: $d(A, B) + d(B, C) \geq d(A, C)$.

We measure the distances between the instance covariance matrix to be classified and the covariance matrices in the train database. k nearest samples from the train database is chosen and the query instance is assigned to the class most common amongst these k samples from the train database. If $k = 1$, then the query instance is assigned to the class of its nearest neighbor.

The choice of k depends on the data. Large values of k with respect to the number of samples decrease the probability of misclassifying and decrease the effect of noise. However it makes the classification boundary less distinct.

4.3.4 Classification Results

Brodatz texture database is a challenging database with lots of non-uniform texture images. For comparison of our codifference matrix method with the original covariance matrix method, we choose 100 randomly sized regions from random locations from each image in the train set. Covariance and codifference matrices are extracted from these random regions and added to the train set. Then the same procedure is repeated for composing the query set. For different values of k, samples in the query set are classified by using k-nn algorithm in both covariance and codifference feature space. Results are listed in Table 4.1

Table 4.1: Comparison of success rates of each method in Brodatz texture database

	Covariance Matrix	Codifference Matrix
k=5	213/222 %95.9	209/222 %94.1
k=10	214/222 %96.3	215/222 %96.8
k=20	214/222 %96.3	215/222 %96.8

In [16], covariance method seems to achive better results in Brodatz texture database. However, since each texture is represented by covariance and codifference matrices extracted from random locations, these small differences in results are possible.

4.4 Plate Recognition

Porikli also used covariance matrix method for license plate recognition problem [28]. In order to compare our codifference matrix with Porikli's method, we test two methods with two different license plate database.

4.4.1 License Plate Databases

First license plate dataset contains plate images gathered from an internet page which contains galleries of used cars for sale (arabam.com). License plate images taken from this website have different illumination, are at different scales and taken from different angles. That is to say, this dataset is a challenging dataset. This database contains Turkish license plate samples. Some sample images from this database is shown in figure 4.3.

The second dataset is taken from Porikli's dataset with his permission. It is very similar to the dataset used in [28] except the negative samples since negative samples are taken randomly from non-plate regions in car images. The license plate images in this database have different illumination, however they are taken at similar angles and are at the same scale. This dataset contains license plates images from USA. Some sample images from this database is shown in figure 4.4.

Figure 4.3: Sample images from license plate database 1

Figure 4.4: Sample images from license plate database 2

The negative samples for train and query datasets are obtained randomly from car pictures with blackened or removed license plates. In order to simulate real life conditions, we use greater number of negative samples with respect to the number of positive samples, in both train and test stages.

4.4.2 Matrix Coefficients

The covariance and codifference matrix coefficients used in this problem contains 7 features. x and y corresponds to the rectangular coordinates of the pixels, I corresponds to the intensity value, and I_x, I_y, I_{xx}, I_{yy} corresponds to the first and second order derivatives of intensity values.

$$C = [\ |x|\ |y|\ |I|\ |I_x|\ |I_y|\ |I_{xx}|\ |I_{yy}|\ ] \tag{4.12}$$

x and y values are all normalized to [0 1], in order to gain scale robustness in images. Therefore $cov(x,x)$,$cov(y,y)$ and $cov(x,y)$ values are always constant for

Table 4.2: Number of train and query samples in license plate database 1

Database I		
	Positive Samples	Negative Samples
Train	99	800
Query	90	800

Table 4.3: Number of train and query samples in license plate database 2

Database II		
	Positive Samples	Negative Samples
Train	240	2400
Query	173	1730

all images. So, for 7 features shown in equation 4.12, we end up with 25 different covariance values.

4.4.3 Classification by Neural Network

We employ a three layer neural network algorithm for classification task. Neural network outputs a numerical result in the range [-1,1] to decide if the region corresponds to a license plate or not.

Our neural network consists of three layers, input layer, hidden layer and the output layer. We used 25 neurons in the input and hidden layers as the size of the input vector. There is only 1 neuron in the output layer for computing the result of the neural network. Our neural network uses supervised learning and backpropagation algorithm for training.

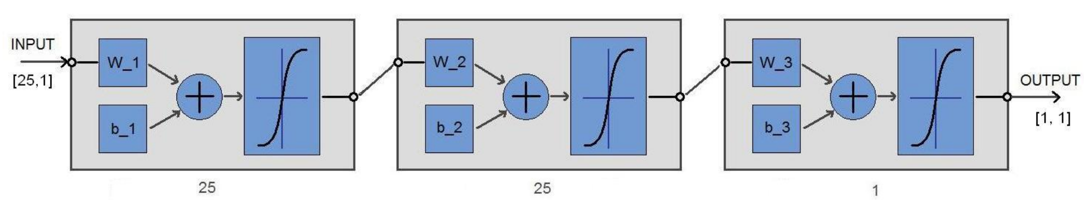


Figure 4.5: Neural Network

The neural network uses a sigmoid function in equation 4.13

$$tansig(z) = \frac{2}{1+e^{-2z}} - 1 \tag{4.13}$$

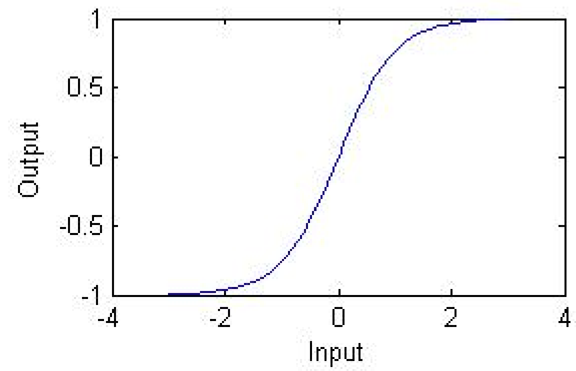


Figure 4.6: Sigmoid function used in neural network as an activation fuction

We use exponentially decreasing learning constant c, as the number of iterations increase.

$$c = 0.1e^{i/1000} \tag{4.14}$$

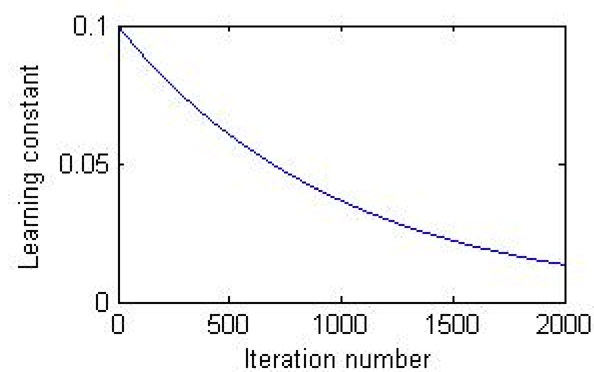


Figure 4.7: Exponentially decreasing learning constant used in backprogation algorithm for training the neural network

For training phase, we use samples from each class, license plate images and non license plate images. Pixel-wise features of these images are computed and covariance and codifference matrices are formed from these values. Non-repeating and non-constant values are removed and the remaining coefficients are used for forming the feature vector of each image. Then with -1 and 1 labels respectively for non plate and plate images, these feature vectors are fed to the neural network. A feed-forward back propagation algorithm is used for updating the weight matrices.

4.4.4 Classification Results

We use a threshold on the result of the neural network in order to decide if the query image corresponds to a plate or not. Since output is in the range [-1 1], this threshold value is 0 by default. Table 4.4 presents the results of two methods.

Table 4.4: Overall success rates of 2 methods in the query sets of the license plate databases

	Database 1	Database 2
Covariance Matrix	% 96.4	%99.0
Codifference Matrix	% 97.3	%99.3

In order to obtain ROC curves, we ordered the query samples according to the output values of the neural network. We divide this ordered sequence from every possible location. Than the part with higher values are labeled as positive results and the part with lower values are labeled as negative results. At each different division, number or true positives and true negatives are computed and marked on the ROC graph. In other words, we changed the threshold value between -1 to 1 and plot the success rates for positive and negative success rates. As we move right-down on the ROC curves, the threshold value decreases, as we move left-up on the ROC curves, threshold value increases. Figure 4.8 and figure 4.9 represent the ROC curves of two methods in the first and in the second license plate databases respectively.

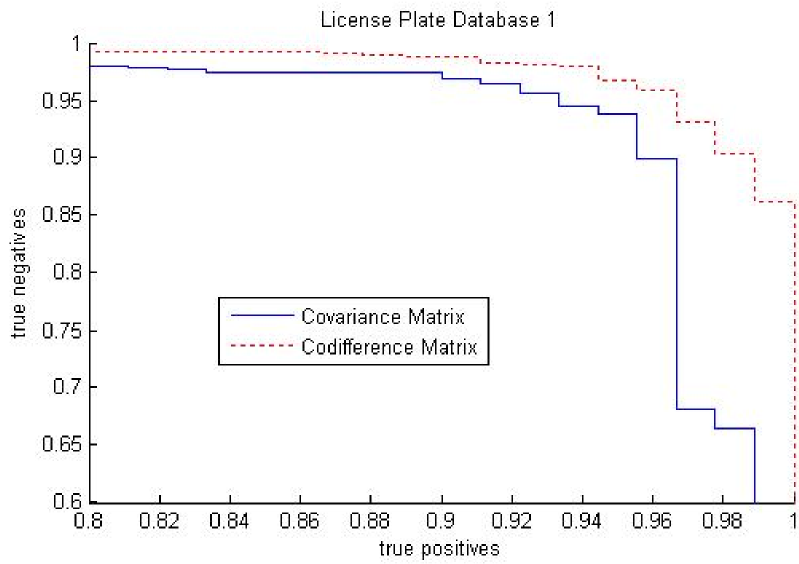


Figure 4.8: ROC curve of original covariance matrix method and codifference matrix method in license plate database 1

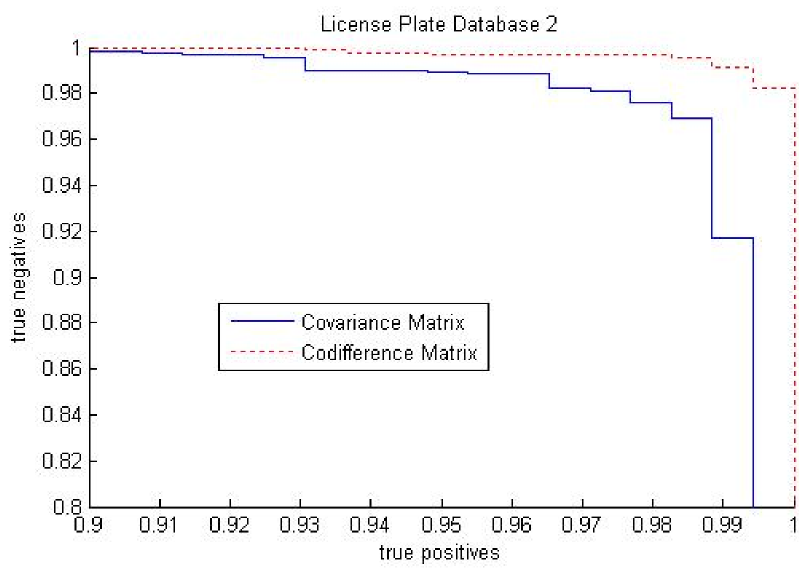


Figure 4.9: ROC curve of original covariance matrix method and codifference matrix method in license plate database 2

Results show that our codifference matrix descriptor gives very similar results to original covariance matrix descriptor. Also, modified method has a lower computational cost advantage over the original one.

4.5 Computational Cost Comparison

The computational cost of the codifference method is lower than the covariance method because it does not require any multiplications. This is especially important in real time applications in which the entire image or video frame has to be scanned at several scales to determine matching regions and ASIC implementations [29, 30, 31].

Table 4.5 describes the computational cost of the covariance method and the codifference method for an image region having N pixels. Each pixel has M features. Therefore the resulting covariance and codifference matrices are M by M. Table 4.6 is a simplified version of the table 4.5 assuming $N \gg M$.

Table 4.5: Computational cost of the covariance and codifference methods for a region with N pixels and M features (Division is actually not necessary for an image description applications $(N-1)\mathrm{c}(i,j)$ or $(N-1)\mathrm{s}(i,j)$ can be be used.)

	Covariance Matrix	Codifference Matrix
Sum	$\frac{3M^2N+NM-M^2-M}{2}$	$\frac{4M^2N+2NM-M^2-M}{2}$
Multiplication	$\frac{M^2+M}{2}N$	0
Sign Comparison	0	$\frac{M^2+M}{2}N$
Division	$\frac{M^2+M}{2}$	$\frac{M^2+M}{2}$

Table 4.6: Simplified version of Table 4.5 assuming $N \gg M$

	Covariance Matrix	Codifference Matrix
Sum	$\frac{3M^2+M}{2}N$	$\frac{4M^2+2M}{2}N$
Multiplication	$\frac{M^2+M}{2}N$	0
Sign Comparison	0	$\frac{M^2+M}{2}N$

Chapter 5

CONCLUSIONS

In this thesis, we studied feature extraction methods for recognition and classification of objects and texture in images.

Object detection and recognition system is designed for real time video systems. We integrated our object classification system with a real-time object detection and tracking system and operated in real time videos. The system uses shapes of the objects for classification. Therefore it is robust against the color and texture of the detected objects. However, it is very sensitive to improper extraction of the object silhouettes, which makes it more appropriate for static indoor environments or for outdoor environments with limited view, like parking lots, stations etc. The system can be upgraded by adding color and texture information for better classification results.

For texture classification system, we modified a previous approach, covariance matrix, by lowering its computational cost. We call this new matrix as codifference matrix. Using a commonly used brodatz texture database and two license plate picture databases, we compared the covariance and the codifference matrix methods. Experiments show that modified method performs as well as the original method with a lower computational complexity. It can be used in embedded systems with a limited computational power or in ASIC (Application Specific Integrated Circuit) implementations more efficiently than the original method.

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