DETECTION OF FORBIDDEN OBJECTS IN X-RAY IMAGES

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BY

HAIDER ALZEYADI

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DETECTION OF FORBIDDEN OBJECTS IN X-RAY IMAGES

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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 the thesis “**Detection of Forbidden Objects in X-Ray Images”** submitted by “**Haider ALZEYADI**” and that in our opinion it is fully adequate, in scope and quality, as a thesis for degree of Master of Science.

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I declare and guarantee that all data, knowledge and information in this document has been obtained, processed and presented in accordance with academic rules and ethical conduct. Based on these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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ABSTRACT

DETECTION OF FORBIDDEN OBJECTS IN X-RAY IMAGES

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Detection of forbidden objects in x-ray scan images has become an important issue for customs border and airport security. Most border screening depends on the manual detection of possible forbidden objects by human experts.

In this thesis, we present a system for detection of possible forbidden objects in x-ray scan images with minimal amounts of missing object (false negatives) and false alarms (false positives). Firstly, pre-processing steps are applied to obtain a clearer image. Then, segmentation is used to locate the potential objects in images. Feature extraction with two algorithms, local binary pattern and histogram oriented gradients, and classification with support vector machine are next steps in the system.

The system is tested using handguns as the forbidden objects in question. The experimental results show that the system can effectively detect the handguns in x-ray scan images with minimal amounts of missing objects automatically.

Keywords: *Forbidden objects, X-ray scan images, Preprocessing, Segmentation, Feature extraction, Classification, Handguns, Customs border security, Airport security*

ÖZ

X-RAY GÖRÜNTÜLERİNDE YASAK NESNELERİN TESPİT EDİLMESİ

ALZEYADI, Haider
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X-ray görüntülerinde yasak nesnelerin tespit edilmesi sınır gümrüğü ve hava alanı güvenliği açısından önemli bir konu haline gelmiştir. Çoğu sınır görüntülemesi yasak nesnelerin uzman insanlar tarafından manuel yolla tespit edilmesine bağlıdır.

Bu tezde, X-ray görüntülerindeki muhtemel yasak nesnelerin minimum kaçak (yanlış negatifler) ve minimum yanlış alarmla (yanlış pozitifler) tespiti için bir sistem sunulmaktadır. Önerilen sistemde öncelikle, daha net bir görüntü elde etmek için ön işleme adımları uygulanmaktadır. Daha sonra, görüntülerdeki muhtemel nesneleri belirlemek için bölütleme kullanılmaktadır. İki algoritmalı öznitelik çıkarımı (lokal ikili biçim ve yönlü gradyan histogramları) ve destek vektör makineli sınıflandırma sistemdeki diğer aşamalardır.

Sistem, yasak nesne olarak tabanca ile test edilmiştir. Deney sonuçları, sistemin, x-ray görüntülerinde tabancaları minimum kayıpla otomatik olarak tanıyabileceğini göstermektedir.

Anahtar kelimeler: *Yasak nesneler, X-ray tarama görüntüleri, Ön işleme, Bölütleme, Özellik çıkarımı, Sınıflandırma, Tabanca, Sınır gümrüğü güvenliği, Hava alanı güvenliği*

To My Family and Friends

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LIST OF ABBREVIATIONS

AI – Artificial Intelligence

CAT-Computerized Axial Tomography

EM – Electromagnetic

FKM- Fuzzy K-Means

HOG-Histogram Oriented Gradients

LBP-Local Binary Pattern

MRI – Magnetic Resonance Image

ORT- Object Recognition Test

SVM – Support Vector Machine

CHAPTER 1

INTRODUCTION

During recent years, Information and Communication Technologies (ICT) have received strong attention from academic and business world. It has become a critical tool for efficient operation, improved performance and quality. With this global aim, organizations start to update and develop their infrastructure components, move from traditional solutions to design and update new technology solutions to create a new and modern environment.

Secure and fast transportation systems are critical for economy and society. In the modern international transport world, border security is given high priority. To support fast movement of passengers and commercials, the governments and organizations have started working on development of effective and efficient rules and techniques in safety sector. Especially, custom and border security, export control, aviation and many other sectors continue to work on the development of new methods and techniques to detect forbidden materials that constitute a direct threat [1]. A safe system is a fundamental component of the global security and it depends directly on effective security screening.

The importance of security has increased in the last years, and this causes to the development of X-Ray screening technology to get over with some potential threats [2]. Not only for custom and border security but also for government organizations, shopping centers, big companies and many others, X-Ray imaging provides a prime tool for checking and inspecting humans and their goods.

X-Ray inspection systems are used to acquire X-Ray images which show the internal structures of objects, and implemented in different domains like medical, industrial, scientific and security applications [3]. They screen objects like luggage and body in customs and border checkpoints for any forbidden objects by checking and analyzing scan images.

Image acquisition is the first process in X-Ray inspection systems [4]. Output images are resources of information. They provide rich information due to their wide range of spectral bands. However, they need a careful inspection and analysis to benefit from the advantages of this information. Today, X-ray image screening systems are still operator-based. That is, the taken images are evaluated manually by operators. These devices are very common in places requiring controlled access like building entrance, airports, and public events. The operator’s performance, decision making, and judgment play a major role in the traditional security systems. Certainly, the human recognition system is stronger than any other systems. However, it is also open to make mistakes depending on different factors. For example, in a complex image, it may be difficult to recognize every detail of objects in the image. Also, according to the many reports, many factors may affect human performance negatively. Such limitations include in sufficient training, loss of motivation and work satisfaction, fatigue, workplace conditions, as well as general human perception and performance limitations. Moreover, studies have shown that human eyes, when worked over a certain period, become tired and fatigued. Similarly, when humans keep on working at one stage, they certainly waste their energy and get tired with the monotonous operations to be carried out. That leads the employees reading and analyzing information wrongly which causes unintentional mistakes. Therefore, to improve security systems, it is essential to have enhanced and sophisticated systems using new technologies. X-Ray scanning systems can be extended by an automatic object recognition system which uses image processing techniques. Such a system can be used to compensate operator mistakes, and even to replace operators or to reduce the number of operators when the success rate of the system reaches to a certain level.

Many researchers work on topics related to image processing such as image pre-processing, image segmentation, object recognition and data extraction from pictures. Image pre-processing includes activities such as contrast stretching, histogram equalization, noise elimination, smoothing using morphological analysis and scaling to manipulate an image so that the result is more suitable than the original one for a specific application. Pre-processing is important because of its contribution to the following processes [5]. Segmentation procedures partition an image into its constituent parts or objects. Segmentation is often the most critical step in image analysis and classification because it aims at discovering objects or parts of objects in images [6][7]. It segments the image into different regions so that they can be used to recognize different objects in images. Pixels in a region are similar to each other for some characteristics or computed properties such as intensity, color, or texture. Nearby regions are different for the same characteristics. The output of image segmentation is a set of segments extracted from the entire image. Object classification is another important task in image processing and computer vision. Image classification refers to labeling of images into one of the predefined categories. Classification plays a significant role in information extraction in different applications with a large quantity of data [8]. Classification is a general operation related to categorization, in which classes of objects are recognized, differentiated, and understood. The results of classification mostly depend on image segmentation[9] and feature extraction. There are many classification techniques used for image classification like Support Vector Machine, Fuzzy Classification, Artificial Neural Network and Decision Tree.

The purpose of this thesis is to investigate the detection of forbidden objects in X-ray images using the image processing techniques summarized above. Primarily, we aim at reducing the number of missing objects (false negatives) as much as possible, since it is very critical for security applications. Because missing objects (forbidden objects that could not be detected) may cause unacceptable results. On the other hand, reducing false alarms (false positives) as much as possible is the secondary aim of this study. Since a false alarm requires additional processes such as manual control by a security officer, it is not desirable, but it is not as critical as missing alarms. The contributions of this theses can be specified as follows:

- X-Ray imaging systems are widely used for security purposes. However, detection of forbidden objects mostly depends on operators watching and inspecting X-Ray images on monitors. Such systems are very sensitive for human mistakes. Automatic detection can be used to enhance X-Ray inspection systems. However, we need to know the achievement of automatic detection using today’s technology and this study is important indication for that purpose.
- Although there are many studies on image processing, only a limited number of studies have focused on security X-Ray images. There are only several

studies which examine automated detection of forbidden objects in X-Ray images. Therefore, the contribution of this study to the security domain is important.

This thesis is organized as follows: In Chapter 2, a literature survey is presented briefly. In chapter 3, techniques used in this study are explained. Test results and discussion are provided in Chapter 4. Finally, conclusions and future studies are given in Chapter 5.

CHAPTER 2

LITERATURE SURVEY

Existing studies in this field proposed different techniques related to image processing to detect hidden objects in X-ray images. Different studies have been done to detect different types of forbidden objects such as hidden weapons, knives, and explosives.

Shen et al [10] presents the application of primary unsupervised classification algorithm for the segmentation of indoor passive Terahertz images of a person with hidden weapons under clothing using single-pixel row-based raster scanning. Several weapons remained hidden under different fabrics types like cotton, polyester, wind blocker jacket and warm sweater. To automate detection, some image processing and pattern recognition techniques are applied, and the results are presented. The proposed algorithm is capable of detecting dielectric objects hidden under clothing. Additionally, they show that pre-processing can reveal low-temperature contrast features, such as folds in clothing.

Elsdon et al [11] work to provide a new technique for imaging hidden metal objects such as weapons by the tripartite technical dimensions indirect, who are usually working on optical frequencies. Imaging objects at microwave frequencies can be proper. This technique is used to define the location and shape of hidden objects. Microwave imaging techniques are expensive. In any case, the researchers have found their straightforward way to detect hidden weapons and compared with other studies.

Kase [12] works using some techniques where the author explores the effect of color coding sketch for the detection of a set of scope threat objects in X-ray images of bags. He maintains that the use of color effectively will not only help screeners to detect more easily without many strain threat objects but will also increase the efficiency of baggage inspection by reducing the time required to carry out inspections and reducing the likelihood of errors due to fatigue.

Sadah et al [13] propose a hybrid method to enhance digital images of X-rays through the pursuit of optimal spatial, frequency and image enhancement formulations. Selected method includes Terahertz imaging which makes it possible to obtain images of objects hidden under clothing by measuring the degree of radiative heat from different objects. The aim of the work is to automatically detect and segment hidden objects in 0.1 to 1 THz images. This is due to the inveterate physical properties in terahertz imaging and passive devices associated with them. Standard segmentation algorithms can slide or detect objects concealed. The work relies on two stages: (1) Using anisotropic algorithm to remove noise from an image then reveal the limits of the hidden objects. (2) Using of Gaussian density to model the temperature distribution within the image. Moreover, it develops curves along isocontours image to get the hidden objects. Also, the authors compare the new approach with two methods indivisible state-of-the-art. Both ways failed to locate hidden objects, while the new method has objects accurately. The new work was more accurate than the state-of-the-art algorithm requiring that the hidden objects already identify. The proposed system is uncensored and can completely operate in real time on the dedicated hardware.

Khan and Chai [14] propose a new approach to filtration the high and low X-ray image energy, remove noise and enhance the image fused with a histogram to improve contrast. The results indicate that the final image did not just contain the details, but it is also the background and an improved contrast noise-free, and thus became the images easier to automatically segment or interpretation by the screeners, therefore reducing the false alarm rate in the baggage inspection X-ray.

The new system proposed by Appleby et al [15] can detect threats, which are fake with liquid and metal or ceramic used an array of millimeter wave technology and cylindrical. The holographic algorithm provides coverage to fill the body of a person in the near real-time and ideally suited to the centers for collective transport such as airport checkpoints that require high and full coverage. The productivity rates determine the algorithm and segment threats site and put them on the research areas wire-frame representation. This algorithm includes artificial neural networks, image processing and edge detection.

Sheen et al [16] work on developing imaging system in wideband millimeter-wave which allows speedy inspection of hidden handguns, explosives, and other threats. They propose a new electromagnetic (EM) solution for the detection of hidden weapons at a distance whether it is a gun, knife, box cutter, and others, each with a unique set of electromagnetic characteristics. Hidden weapons should be detected at a distance and the solution lies in the use of signals on the frequency and wide millimeter wave. The natural resonances signature is unique for special materials and that can be used to describe the object. Using these signals excitement in the frequency band mm-wave, such as the decision to increase the benefits and reduce the size of the item can be realized. Also, the use of broadband signal-mm wave excitation provides signature EM promote the goal of which displays more features to classify the object.

Novak et al [17] worked on a method to determine the hidden threats whether there are handguns, knives, each having a unique set of electromagnetic characteristics. They develop new ways to detect non-metallic weapons such as pistols and explosives ceramics to secure public places. They use millimeter-waves. They developed a multi-sensor based on a high cavity. It relies on the contrast between the refractive human body and refractive of insulators.

Weiet al [18] work to provide an algorithm to increase the quality of millimeter wave of the video sequence to detect hidden weapons, by dividing video frame in the foreground and background region, and then work with them differently. A probabilistic system for image fusion based on statistical signal processing approach. They experimented with this method for applications detect hidden weapons. The results showed the advantages of EM- based approach in some cases. When they apply the algorithm on cases having multiple frames of video sequences, it can be expected as a result of fused improved over the cases. The multiple frames provide redundant information on the right scene. Extra information is very helpful in the estimation. They also envision some other improvements in the current fusion approach. If build a model for image composition may distort correlated Gaussian mixture, and that this model should be closer to the sensing images and the realistic estimate has improved.

Xueet al. [19] work on developing a new visual image algorithm to fuse a color and corresponding Infrared (IR) images for hidden weapons detection systems. The fused image is obtained by the new color image fusion algorithm, proposed to control a high-resolution optical image, and the integration of any hidden weapons detected by sensors infrared, and maintain the natural color of the visual image .

M. Singhet al [20] present a methodology to improve the image segmentation algorithms chopping based on image characteristics without manual intervention. Methodology calculates image properties such as the average edge gradient force, the cluster by using features of the color image, and color purity of the region to train a neural network to label resultant segmentation. The methodology works very well by predicting the parameters of the object and algorithms perform good results for real applications

CHAPTER 3

TECHNIQUES USED IN THE STUDY

Figure 3.1 shows a diagram describing the general steps of a system to detect forbidden objects in x-ray images. A human airport luggage screener can decide to make a decision, and help classification. The following briefly provides information for each step of the automatic detection system.

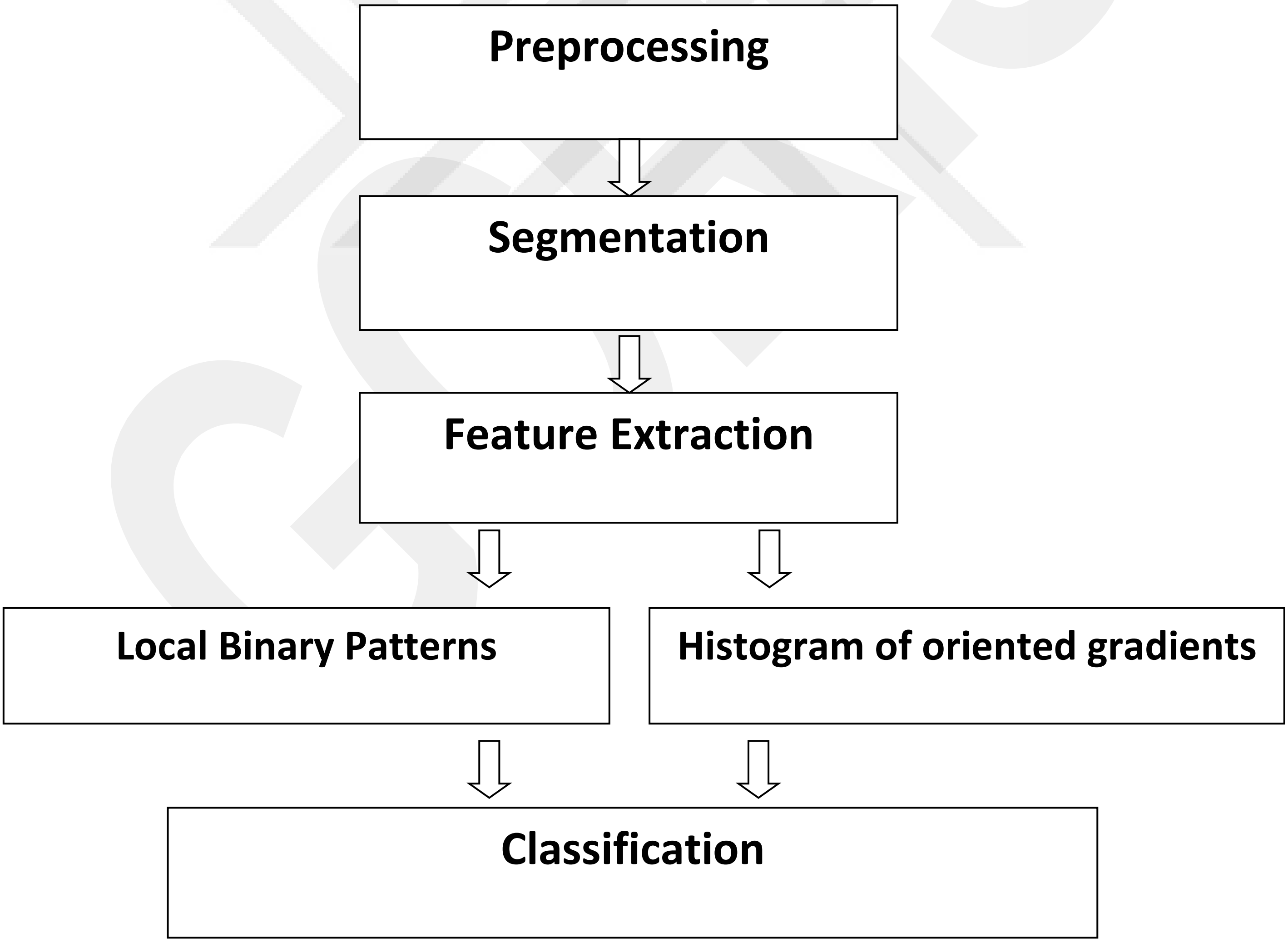


Figure 3.1: System to detect forbidden objects in x-ray images

3.1 Pre-Processing

The aim of the pre-processing of digital image enhancement is to provide a processed image that uses for a specific application. We might need an image that is easy and clear to understand by a human or an image that can be analyzed and interpreted by a computer. There are two different strategies to achieve this goal. First, the image can be displayed properly; this will help a human (or computer) extract the wanted information. Second, the image can be pre-processed so that the required important data is saved and the rest is discard. That needs a definition of the informational part, and it makes an application specific enhancement technique. The request to improve images to help many applications has existed for image processing. Image enhancement is one of the oldest and best fields in image processing.

We define the brightness change in an image using its histogram. Moreover, view at operations which improve the image histogram processes and making the image brighter in different ways. Moreover, the statistical operations can decrease noise in the image, which is one of the interests to the feature extraction techniques to be analyzed later. As such, these basic operations are called pre-processing done to improve image quality before feature extraction.

Histograms play a central role in image processing, in fields such as enhancement, compression, segmentation, and description. The focus of this section is on obtaining, plotting, and using histograms for image enhancement and intensity transformation tasks based on information extracted from image intensity.

In an image processing field, the histogram of the image usually assigns to a histogram of the pixel intensity values. The image histogram is a graph dispensing the number of pixels in the image at each different intensity value found in that image. The correct output from the operation depends on the implementation, it may simply be a plot of the required histogram in a proper image format, or it may be a data file of some sort representing the histogram statistics. Figure(3.2) show histogram statistics for image representation

It may be defined as:

$h\ (r_k) = n_k$

r_k : the gray level,

n_k : the number of pixels in the image having gray level r_k .

$h\ (120_{256})$=10000

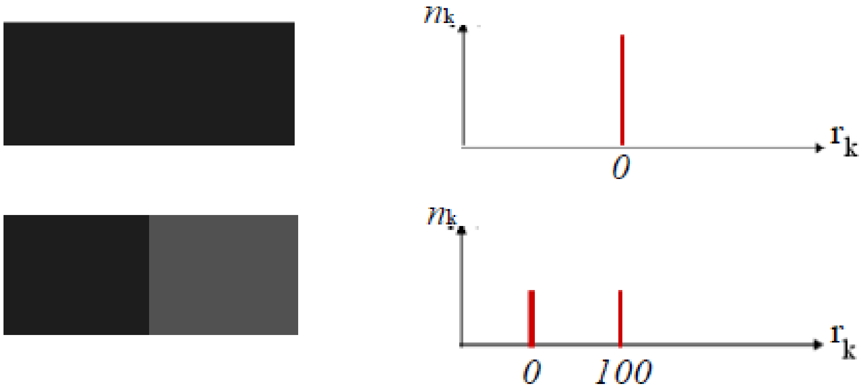


Figure 3.2: histogram statistics for image representation

Where r_k is the kth intensity level in the interval [0, G] and n is the number of pixels in the image where intensity level is r_k. The value of G is 255 for images of class unit8, 65535 for images of class unit16, and 1.0 for floating point images. Note that GL=-1 for images of class unit8 and unit16. Pixels intensity of input images may be modified using some given functions.

Histograms have many uses. One of the more commons is to decide what value of threshold to use when converting a grayscale image to a binary one by thresholding. If the image is suitable for thresholding then the histogram will be bi-modal i.e. the pixel intensities will be clustered around two well-separated values. A suitable threshold for separating these two groups will be found somewhere in between the two peaks in the histogram. If the distribution is not like this then it is unlikely that a good segmentation can be produced by thresholding.

Some histograms distribution will show a skewed distribution to the left, as shown below. A distribution skewed to the left is said to be negatively skewed. This type of distribution has a high number of occurrences in the upper-value cells and few in the lower value cells (left side). This kind of distribution can result when data is collected from a system with a boundary. Figure 3.3 shows histogram modification function.

$$s = T(r) = \int_0^r p_r(w)\,dw$$

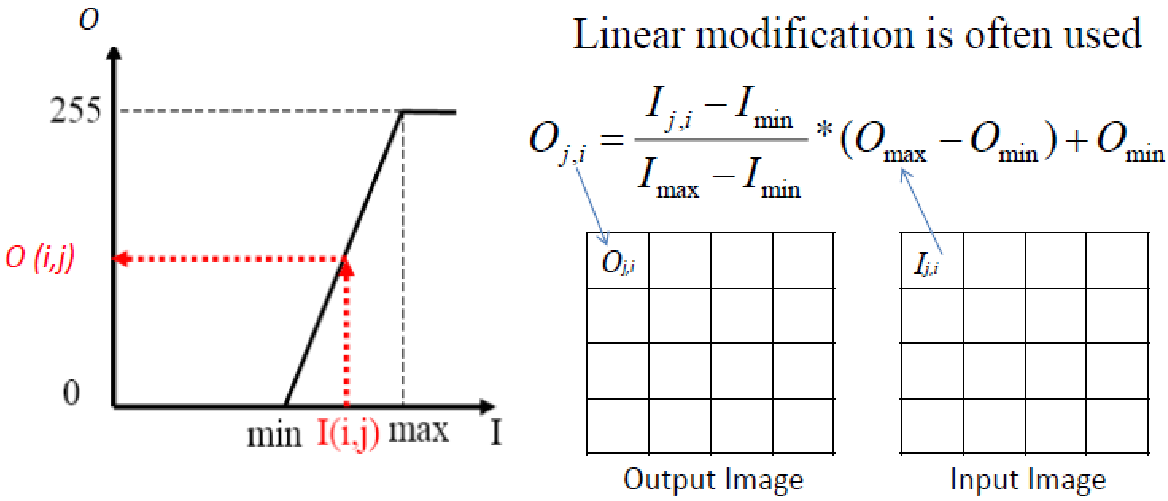


Figure 3.3: Histogram modification function

Sometimes it is necessary to work with normalized histograms, obtained simply by dividing all elements by the total number of pixels in the image, which we denote by n:

$$\begin{aligned} p(r_k) &= \frac{h(r_k)}{n} \\ &= \frac{n_k}{n} \end{aligned}$$

Assume for a moment that intensity levels are continuous quantities normalized to the range [0, 1], and let pr(r) mean the probability density function (PDF) of the intensity levels in an input image, where the index used for separating between the PDFs of the input and output images. Assume that we perform the following transformation on the input levels to obtain output (processed) intensity levels, s,

$$p_s(s) = \begin{cases} 1 & \text{for } 0 \le s \le 1 \\ 0 & \text{otherwise} \end{cases}$$

In other words, preceding transformation produces equal intensity levels in the images are achievable, and, also, include the whole range [0, 1]. The resting result of this intensity-level equalization process is an image with improved effective range, which will direct to have higher contrast. See that the transformation function is nothing more than the cumulative distribution function (CDF).

When dealing with discrete numbers, we work with histograms and call the preceding technique histogram equalization, although, in general, the histogram of the processed image will not be uniform, due to the discrete nature of the variables.

In a given image, the rates in a normalized histogram are approximations to the probability of occurrence of each intensity level in the image. For discrete quantities, we work with summations, and the equalization transformation becomes

$$\begin{aligned} s_k &= T(r_k) \\ &= \sum_{j=0}^{k} p_r(r_j) \\ &= \sum_{j=0}^{k} \frac{n_j}{n} \end{aligned}$$

To improve the contrast in an image, it is recommended to equalize its histogram (Figure 3.4).

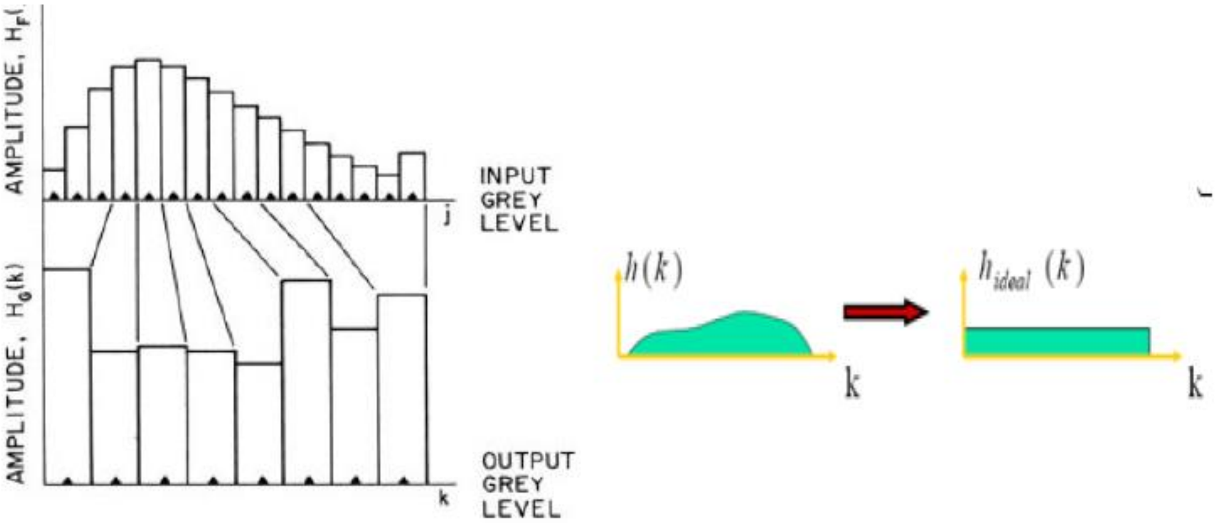


Figure 3.4: Histogram modification

When dealing with discrete numbers, we work with histograms and call the preceding technique histogram equalization, although, in general, the histogram of the processed image will not be uniform

Main principle steps

Step 1: Histogram determination

$$h(i) \quad i \in [0,255]$$

Step 2: Divide by the pixels number to find normalized histogram [0,1]

$$h_n(i) = \frac{h(i)}{Nbp} \quad i \in [0,255]$$

Step 3: Find the probability density of Normalized Values

$$C(i) = \sum_{j=0}^{i} h_n(j) \qquad i \in [0,255]$$

Step 4: Transformation in to gray scale image

$$f'(x,y) = C(f(x,y)) \times 255$$

In part of image Some part of image but an equalization step has been applied and part of grayscale image pixel intensity are coded using only 3 bits Figure (3.5).

$$\begin{bmatrix} 1 & 3 & 5 & 5 & 7 \\ 5 & 3 & 3 & 5 & 3 \\ 3 & 6 & \textcircled{6} & 6 & 6 \\ 1 & 5 & 7 & 3 & 3 \end{bmatrix} \qquad \begin{bmatrix} 0 & 1 & 2 & 2 & 6 \\ 2 & 1 & 1 & 2 & 1 \\ 1 & 3 & \textcircled{4} & 3 & 3 \\ 0 & 2 & 5 & 1 & 1 \end{bmatrix}$$

Figure 3.5: Some part of image but an equalization step has been applied and part of grayscale image pixel intensity are coded using only 3 bits

Let’s take the Pixel P(3,3) = 4 as an example First step: calculate the histogram h(4) as in the table Second step : divide each value by the total number of all pixels

	h(i)	$h_n(i)$
0	2	2/20
1	7	7/20
2	5	5/20
3	3	3/20
4	1	1/20
5	1	1/20
6	1	1/20

In third step:

$$c(4) = \sum_{i=0}^{4} h_n(i)$$
$$= \frac{2}{20} + \frac{7}{20} + \frac{5}{20} + \frac{3}{20} + \frac{1}{20} = \frac{18}{20}$$

And in forth step: as the pixel intensity is coded by 3 bits, the maximal gray levels will be 7. Thus the new value of P(3, 3) will be :

Peq(3,3) = c(4) * 7= (18/20) * 7 = 6

Using the same steps over all the pixels, new equalized image will be given

3.2. Segmentation

The division of an image into significant structures, image segmentation, is often an essential step in image study, object representation, visualization, and many other image processing tasks. We will converge on methods that find the particular pixels that make up an object.

There are different segmentation methods suggested in the past decades, and some categorization is important to present the methods properly here. A disjunct categorization does not appear to be possible, though, because even two very different segmentation approaches may share properties that defy unique categorization. The categorization presented in this part is therefore rather a classification regarding the importance of an approach than a strict division.

Thresholding is apparently the most frequently used technique to segment an image. The thresholding operation is a gray value remapping operation g defined by

$$g(v) = \begin{cases} 0 & \text{if} \quad v < t \\ 1 & \text{if} \quad v \geqslant t, \end{cases}$$

Where v represents a gray value, and t is the threshold value. Thresholding charts a grey-valued image to a binary image. Later the thresholding operation, the image has been segmented into two segments, identified by the pixel values zero and one respectively.

For an image which contains bright objects on a dark background, thresholding can be applied to segment the image. For varied types of images, the gray values of objects are very unusual from the background value; thresholding is usually a well-suited method to segment an image into objects and background. If the objects are not overlapping, then we can create a separate segment from each object by running a labeling algorithm from the thresholded binary image, thus assigning a unique pixel value to each object.

Several methods used to select a suitable threshold value for a segmentation duty. Possibly the most common method is to set the threshold value interactively; the user is managing the value and evaluating the thresholding result until a satisfying segmentation has been achieved. The histogram is often a valuable tool in establishing a suitable threshold value.

Histogram and the thresholding results using four different threshold values obtained from the histogram. Image segments can be identified by their grey values, threshold segmentation can be increased to use different thresholds techniques to classify an image into 2 segments, the pixels with values between the first and second threshold are assigned to segment one, all pixels with a value smaller than the first threshold are assigned to segment zero, all pixels with values between the second and third threshold are assigned to segment 2, etc. If n thresholds (t1, t2, . . . ,tn) are used:

$$g(v) = \begin{cases} 0 & \text{if} \quad v < t_1 \\ 1 & \text{if} \quad t_1 \leqslant v < t_2 \\ 2 & \text{if} \quad t_2 \leqslant v < t_3 \\ \vdots & \quad \vdots \qquad \vdots \\ n & \text{if} \quad t_n \leqslant v. \end{cases}$$

3.3. Feature extraction

In machine learning, pattern recognition and image processing, feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations. Feature extraction is related to dimensionality reduction.

When the input data to an algorithm is too large to be processed, and it is assumed to be redundant, then it can be transformed into a reduced set of features. Determining a subset of the initial features is called feature selection. The selected features are required to contain the relevant information from the input data so that the necessary task can be executed by using this reduced representation instead of the complete initial data.

The problem of how to access and manage non-textual information is progressively apparent as expressed by the nature of image data, the storage requirements, the image representations, and the rapid growth of the use of image data is a representative for multimedia data. Firstly, the nature of images is totally different from numerical and textual data, so existing solutions are not directly applicable to images. To solve the problems, an image descriptor or "key" is given for image identification. In fact, visual properties are difficult or nearly impossible to describe with text. Also, there is no commonly agreed-upon vocabulary for describing image properties, so a Structured Query Language (SQL) is simply not the case for image searching. Moreover, user requirements to access the same image are different. For example, one may need to find a specific object within the image whereas another one may look for spatial relationships among regions or objects. Huge storage requirement is an inherited property of images. The requirement also poses storage and access constraints in the use of a shared collection of images. The situation may lead to overall degradation of network response time.

Image representation does not support access and management of image data. From the information management aspect, a large data stream is a considerable hindrance, so compression techniques are required. State of the art compression techniques can compress images as compact as the statistical entropy. The techniques depend on image models. The models represent images regarding pixel values or groups of pixels rather than semantic entities. That deprives image meaning and makes image identification based on content becomes difficult. Meaning is obscure, and the access of image is problematic. Therefore, it is clear that the techniques achieve a high degree of compression, regardless of the information. Finally, users rapidly migrate from textual data services to multimedia services. This stems from two main reasons. Firstly, multimedia presentation perceptually conveys information. This makes an efficient communication process, and most information is comprehensive. This forms the new medium for information interchange. Secondly, a global network for information interchange is available. The Internet is the biggest network connecting the world. The Internet services such as world-wide-web encourage the interchange of information among users. That is more so when users have easily understandable data stream.

Local binary patterns

Local binary patterns (LBP) is a type of visual descriptor used for classification in computer vision. LBP is the particular case of the Texture Spectrum model proposed in 1990 [22][23]. LBP was first described in 1994 [24][25]. It has since been found to be important for texture feature classification; it has more determined that when LBP is combined with the Histogram of oriented gradients (HOG) descriptor, it improves the detection performance considerably on some datasets [26]. A comparison of several improvements of the original LBP in the field of background subtraction was made in 2015 by Silva et al [27].

The LBP feature vector, in its simplest form, is created in the following manner:

- Divide the examined window into cells (e.g. 16x16 pixels for each cell).
- For each pixel in a cell, compare the pixel to each of its 8 neighbors (on its left-top, left-middle, left-bottom, right-top, etc.). Follow the pixels along a circle, i.e. clockwise or counter-clockwise.

- Where the center pixel's value is greater than the neighbor's value, write "0". Otherwise, write "1". This gives an 8-digit binary number (which is usually converted to decimal for convenience).
- Compute the histogram, over the cell, of the frequency of each "number" occurring (i.e., each combination of which pixels are smaller and which are greater than the center). This histogram can be seen as a 256-dimensional feature vector.
- Optionally normalize the histogram.
- Concatenate (normalized) histograms of all cells. This gives a feature vector for the entire window.

The feature vector can now be processed using the Support vector machine or some other machine-learning algorithm to classify images. Such classifiers can be used for face recognition or texture analysis.

An excellent extension to the original operator is the so-called uniform pattern[28], which can be applied to reduce the length of the feature vector and perform an easy rotation invariant descriptor. This approach is motivated by the case that some binary patterns occur more usually in texture images than others. A local binary pattern is called uniform if the binary pattern includes at most two 0-1 or 1-0 transitions. For model, 00010000(2 transitions) is a uniform pattern, 01010100(6 transitions) is not. In the calculation of the LBP histogram, the histogram has a divided bin for every uniform pattern, and all non-uniform patterns are selected to a single bin. Using uniform patterns, the length of the feature vector for a single cell reduces from 256 to 59.

Histogram of oriented gradients

The histogram of oriented gradients (HOG) is a feature descriptor used in computer vision and image processing for the purpose of object detection. The technique counts occurrences of gradient orientation in localized portions of an image. This method is similar to that of edge orientation histograms, scale-invariant feature transform descriptors, and shape contexts, but differs in that it is computed on a dense grid of uniformly spaced cells and uses overlapping local contrast normalization for improved accuracy.

Robert K. McConnell of Wayland Research Inc. first described the concepts behind HOG without using the term HOG in a patent application in 1986[29]. In 1994 the concepts were used by Mitsubishi Electric Research Laboratories[30]. However, usage only became widespread in 2005 when Navneet Dalal and Bill Triggs, researchers for the French National Institute for Research in Computer Science and Automation (INRIA), presented their supplementary work on HOG descriptors at the Conference on Computer Vision and Pattern Recognition (CVPR). In this work they focused on pedestrian detection in static images, although since then they expanded their tests to include human detection in videos, as well as to a variety of common animals and vehicles in static imagery.

The essential thought behind the histogram of oriented gradients descriptor is that local object appearance and shape within an image can be described by the distribution of intensity gradients or edge directions. The image is divided into small connected regions called cells, and for the pixels within each cell, a histogram of gradient directions is compiled. The descriptor is the concatenation of these histograms. For improved accuracy, the local histograms can be contrast-normalized by calculating a measure of the intensity across a larger region of the image, called a block, and then using this value to normalize all cells within the block. This normalization results in better invariance to changes in illumination and shadowing.

The HOG descriptor has a few key advantages over other descriptors. Since it operates on local cells, it is invariant to geometric and photometric transformations, except for object orientation. Such changes would only appear in larger spatial regions. Moreover, as Dalal and Triggs discovered, coarse spatial sampling, fine orientation sampling, and strong local photometric normalization permits the individual body movement of pedestrians to be ignored so long as they maintain a roughly upright position. The HOG descriptor is thus particularly suited for human detection in images [31].

Gradient computation

The first step of calculation in many feature detectors in image pre-processing is to ensure normalized color and gamma values. As Dalal and Triggs point out, however, this step can be omitted in HOG descriptor computation, as the ensuing descriptor normalization essentially achieves the same result. Image pre-processing thus provides little impact on performance. Instead, the first step of calculation is the computation of the gradient values. The most common method is to apply the 1-D centered, point discrete derivative mask in one or both of the horizontal and vertical directions. Specifically, this method requires filtering the color or intensity data of the image with the following filter kernels:

[-1,0,1] and [-1,0,1]T

Dalal and Triggs tested other, more complex masks, such as the 3x3 Sobel mask or diagonal masks, but these masks generally performed more poorly in detecting humans in images. They also experimented with Gaussian smoothing before applying the derivative mask, but similarly found that omission of any smoothing performed better in practice [31].

Orientation binning

The second step of calculation is creating the cell histograms. Each pixel within the cell casts a weighted vote for an orientation-based histogram channel based on the values found in the gradient computation. The cells themselves can either be rectangular or radial in shape, and the histogram channels are evenly spread over 0 to 180 degrees or 0 to 360 degrees, depending on whether the gradient is “unsigned” or “signed”. Dalal and Triggs found that unsigned gradients used in conjunction with 9 histogram channels performed best in their human detection experiments. As for the vote weight, pixel contribution can either be the gradient magnitude itself, or some function of the magnitude. In tests, the gradient magnitude itself generally produces the best results. Other options for the vote weight could include the square root or square of the gradient magnitude, or some clipped version of the magnitude [31].

Descriptor blocks

To account for changes in illumination and contrast, the gradient strengths must be locally normalized, which requires grouping the cells together into larger, spatially connected blocks. The HOG descriptor is then the concatenated vector of the components of the normalized cell histograms from all of the block regions. These blocks typically overlap, meaning that each cell contributes more than once to the final descriptor. Two main block geometries exist: rectangular R-HOG blocks and circular C-HOG blocks. R-HOG blocks are generally square grids, represented by three parameters: the number of cells per block, the number of pixels per cell, and the number of channels per cell histogram. In the Dalal and Triggs human detection experiment, the optimal parameters were found to be four 8x8 pixels cells per block (16x16 pixels per block) with 9 histogram channels. Moreover, they found that some minor improvement in performance could be gained by applying a Gaussian spatial window within each block before tabulating histogram votes in order to weight pixels around the edge of the blocks less. The R-HOG blocks appear quite similar to the scale-invariant feature transform (SIFT) descriptors; however, despite their similar formation, R-HOG blocks are computed in dense grids at some single scale without orientation alignment, whereas SIFT descriptors are usually computed at sparse, scale-invariant key image points and are rotated to align orientation. In addition, the R-HOG blocks are used in conjunction to encode spatial form information, while SIFT descriptors are used singly.

Circular HOG blocks (C-HOG) can be found in two variants: those with a single, central cell and those with an angularly divided central cell. In addition, these C-HOG blocks can be described with four parameters: the number of angular and radial bins, the radius of the center bin, and the expansion factor for the radius of additional radial bins. Dalal and Triggs found that the two main variants provided equal performance, and that two radial bins with four angular bins, a center radius of 4 pixels, and an expansion factor of 2 provided the best performance in their experimentation(to achieve a good performance, at last use this configure). Also, Gaussian weighting provided no benefit when used in conjunction with the C-HOG blocks. C-HOG blocks appear similar to shape context descriptors, but differ strongly in that C-HOG blocks contain cells with several orientation channels, while shape contexts only make use of a single edge presence count in their formulation[33].

In addition, the scheme L2-hys can be computed by first taking the L2-norm, clipping the result, and then renormalizing. In their experiments, Dalal and Triggs found the L2-hys, L2-norm, and L1-sqrt schemes provide similar performance, while the L1-norm provides slightly less reliable performance; however, all four methods showed very significant improvement over the non-normalized data

3.4. Classification

In machine learning, support vector machines (SVMs, also support vector networks[32]) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall.

In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

When data are not labeled, supervised learning is not possible, and an unsupervised learning approach is required, which attempts to find natural clustering of the data to groups, and then map new data to these formed groups. The clustering algorithm which provides an improvement to the support vector machines is called support vector clustering[33] and is often used in industrial applications either when data are not labeled or when only some data are labeled as a preprocessing for a classification pass.

Classifying data is a common task in machine learning. Suppose some given data points each belong to one of two classes, and the goal is to decide which class a new data point will be in. In the case of support vector machines, there are many hyperplanes that might classify the data. One reasonable choice as the best hyperplane is the one that represents the largest separation, or margin, between the two classes. So, we choose the hyperplane so that the distance from it to the nearest data point on each side is maximized. If such a hyperplane exists, it is known as the maximum-margin hyperplane and the linear classifier it defines is known as a maximum margin classifier; or equivalently, the perceptron of optimal stability.

In objects detection and recognition with binary classification, precision (also called positive predictive value) is the division of retrieved instances that are relevant, while recall (also known as sensitivity) is the fraction of relevant instances that are retrieved. Both precision and recall are therefore based on an understanding and measure of relevance.

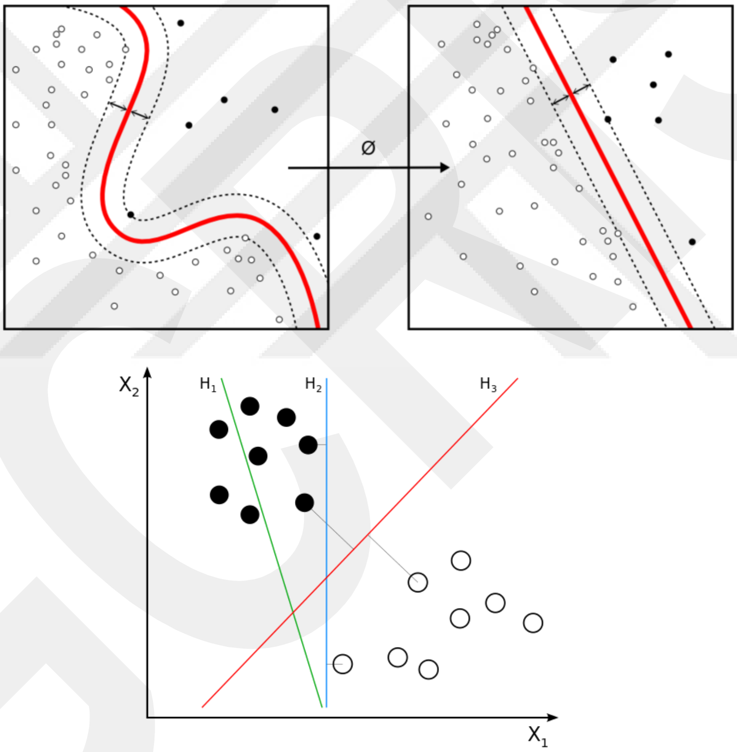


Figure 3.6: SVM classification

In an information retrieval scenario, the instances are documents and the task is to return a set of relevant documents given a search term; or equivalently, to assign each document to one of two categories, "relevant" and "not relevant." In this case, the "relevant" documents are simply those that belong to the "relevant" category. The recall is defined as the number of relevant documents retrieved by a search divided by the total number of existing relevant documents, while precision is defined as the number of relevant documents retrieved by a search divided by the total number of documents retrieved by that search.

Support Vector Machine creates a set of hyperplanes in a high dimensional space, which is used for classification or regression. The good separation is achieved by the hyperplane. SVM uses non-parametric with binary classifier approach and handles more input data efficiently. Accuracy depends on hyperplane selection. The Structure of the SVM algorithm is more complicated than other methods. Figure 3.6 shows SVM classification.

Support vector machines, In machine learning, are supervised learning models with connected learning algorithms that examine data used for classification and regression analysis. Offered a set of training samples, each labeled as belonging to one or the other of two classes, SVM training algorithm creates a model that assigns new examples to one class or the other, giving it a non-probabilistic binary linear classifier. An SVM model is a design of the samples as objects in space, mapped so that the examples of the classify classes are distributed by a clear gap that is as separated as possible. New symbols are then drafted into that same space and predicted to belong to a category based on which side of the gap they fall.

In linear SVM we are given a training dataset of n points of the form

$$(\vec{x}_1, y_1), \ldots, (\vec{x}_n, y_n)$$

$$\vec{w} \cdot \vec{x} - b = 0,$$

where w is a real vector of weights and f is a function that converts the dot product of the two vectors into the desired output. Often f is a simple function that maps all values above a certain threshold to the first class and all other values to the second class. A more complex f might give the probability that an item belongs to a certain class.

If the training data are linearly separable, we can select two parallel hyperplanes that separate the two classes of data, so that the distance between them is as large as possible. The region bounded by these two hyperplanes is called the "margin", and the maximum-margin hyperplane is the hyperplane that lies halfway between them. These hyperplanes can be described by the equations.

To extend SVM to cases in which the data are not linearly separable, we introduce the hinge loss function, the kernel function is a generalization of a positive definite function or a positive-definite matrix. It was first presented by James Mercer the context of determining integral operative equations. Since then positive definite functions and their several analogs and generalizations have resulted in diverse parts of mathematics. They occur naturally in Fourier analysis, probability theory, operator theory, complex function-theory, moment problems, integral equations, boundary-value problems for partial differential equations, machine learning, embedding problem, information theory, and other areas.

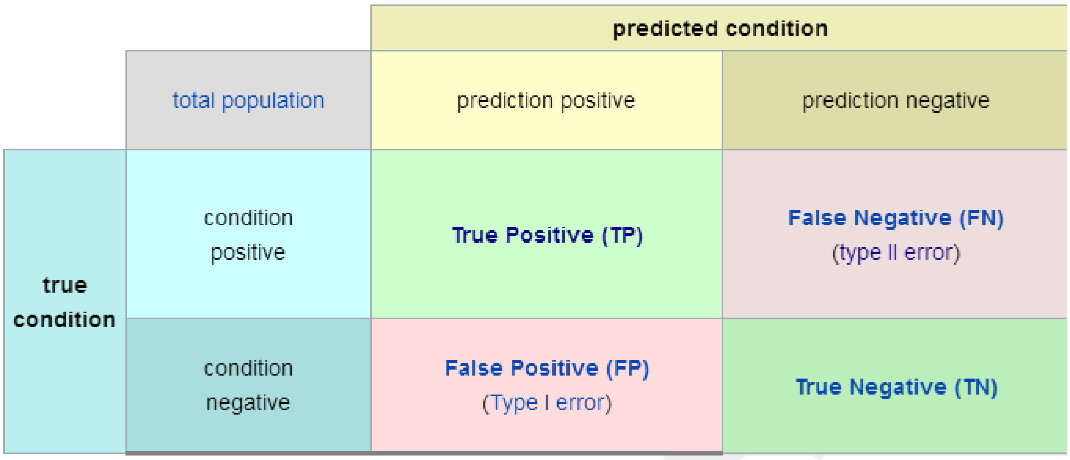
CHAPTER 4

RESULTS AND DISCUSSION

This study aimed at detecting forbidden guns in luggage with minimal amounts of missing object (false negatives) and false alarms (false positives) in classification. Tests are carried out with support vector machine classification using two different features which are local binary pattern (LBP)and histogram of oriented gradients (HOG). This chapter presents the obtained success rates for detecting guns in x-ray images.

Confusion matrix

To measure the performance of machine learning algorithms, confusion matrices are formed. A Confusion matrix is a way of representing consistency of produced output results. The form of such a matrix is given in Table 1. True positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), are the four different possible outcomes of a single prediction for a two-class case. A false positive is when the computed value is incorrectly classified as negative, when it is, in fact, positive. A false negative is when the computed value is incorrectly classified as positive when it is, in fact, negative. True positives and true negatives are obviously correct classifications. Also, “Specificity” measures the proportion of negatives which are correctly identified and “Accuracy” can be seen as the degree of closeness of measurements. “Positive predictive value” measures the probability that a positive result is truly positive and “Negative predictive value” evaluates the probability that a negative result is truly negative. Table1show Form of confusion matrix



		predicted condition	
	total population	prediction positive	prediction negative
true condition	condition positive	**True Positive (TP)**	**False Negative (FN)** (type II error)
	condition negative	**False Positive (FP)** (Type I error)	**True Negative (TN)**

Table1: Form of confusion matrix

In objects detection and recognition with binary classification, precision (also called positive predictive value) is the division of retrieved instances that are relevant, while recall (also known as sensitivity) is the fraction of relevant instances that are retrieved. Both precision and recall are therefore based on an understanding and measure of relevance

In an information retrieval scenario, the instances are documents and the task is to return a set of relevant documents given a search term; or equivalently, to assign each document to one of two categories, "relevant" and "not relevant." In this case, the "relevant" documents are simply those that belong to the "relevant" category. The recall is defined as the number of relevant documents retrieved by a search divided by the total number of existing relevant documents, while precision is defined as the number of relevant documents retrieved by a search divided by the total number of documents retrieved by that search. Table 2 shows the results for support vector machine with local binary pattern, and Table 3 shows the results for support vector machine with histogram oriented gradients. Table 4 shows detection results and Figure 4.1 shows comparison of results.

		Target			
		Positive	Negative		
Model	Positive	79	20	*Precision*	0.84
	Negative	14	67	*Recall*	0.79
		F-measure=0.82		**Accuracy = 0.81**	

Table 2: Results for support vector machine with local binary pattern

		Target			
		Positive	Negative		
Model	Positive	71	23	*Precision*	0.78
	Negative	20	66	*Recall*	0.75
		F-measure=0.77		**Accuracy = 0.76**	

Table 3:results for support vector machine with histogram oriented gradients

	SVM-1(LBP)	SVM-2(HOG)
TP	79	71
TN	67	66
FN	20	23
FP	14	20
Accuracy	0.81	0.76

Table 4**:** Detection results

Figure 4.1: Comparison of results

Accuracy

In the fields of science, engineering, and statistics, the accuracy of a measurement system is the degree of closeness of measurements of a quantity to that quantity's true value. The precision of a measurement system, related to reproducibility and repeatability, is the degree to which repeated measurements under unchanged conditions show the same results. Although the two words precision and accuracy can be synonymous in colloquial use, they are deliberately contrasted in the context of the scientific method.

A measurement system can be accurate but not precise, precise but not accurate, neither, or both. For example, if an experiment contains a systematic error, then increasing the sample size generally increases precision but does not improve accuracy. The result would be a consistent yet inaccurate string of results from the flawed experiment. Eliminating the systematic error improves accuracy but does not change precision.

A measurement system is considered valid if it is both accurate and precise. Related terms include bias (non-random or directed effects caused by a factor or factors unrelated to the independent variable) and error (random variability).

The terminology is also applied to indirect measurements that values obtained by a computational procedure from observed data.

In addition to accuracy and precision, measurements may also have a measurement resolution, which is the smallest change in the underlying physical quantity that produces a response in the measurement.

In numerical analysis, accuracy is also the nearness of a calculation to the true value; while precision is the resolution of the representation, typically defined by the number of decimal or binary digits. Figure 4.2 show Accuracy results

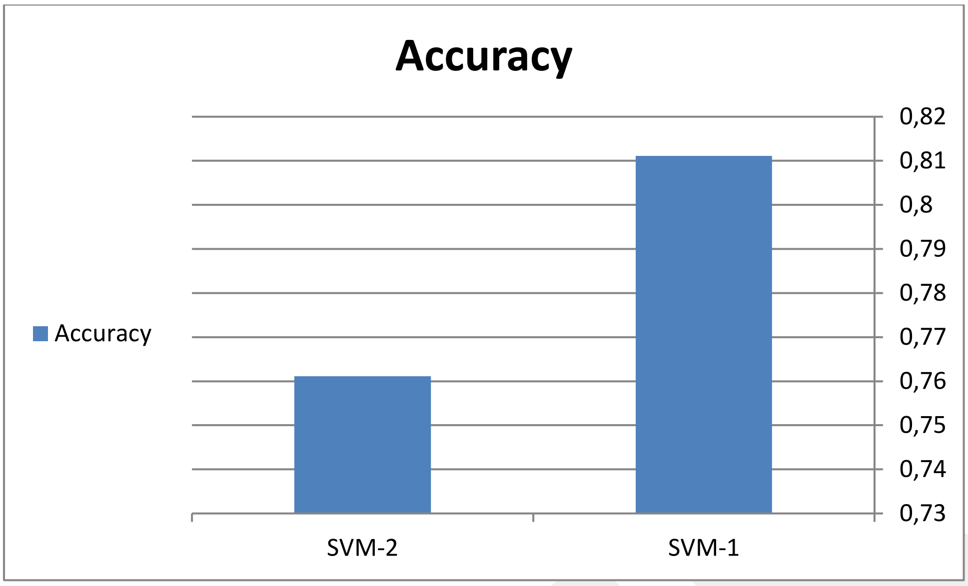


Figure 4.2: Accuracy results

Precision

In the field of information retrieval, precision is the fraction of retrieved documents that are relevant to the query:

$$\text{precision} = \frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{retrieved documents}\}|}$$

Precision takes all retrieved documents into account, but it can also be evaluated at a given cut-off rank, considering only the topmost results returned by the system. This measure is called precision . Figure 4.3 show Precision results

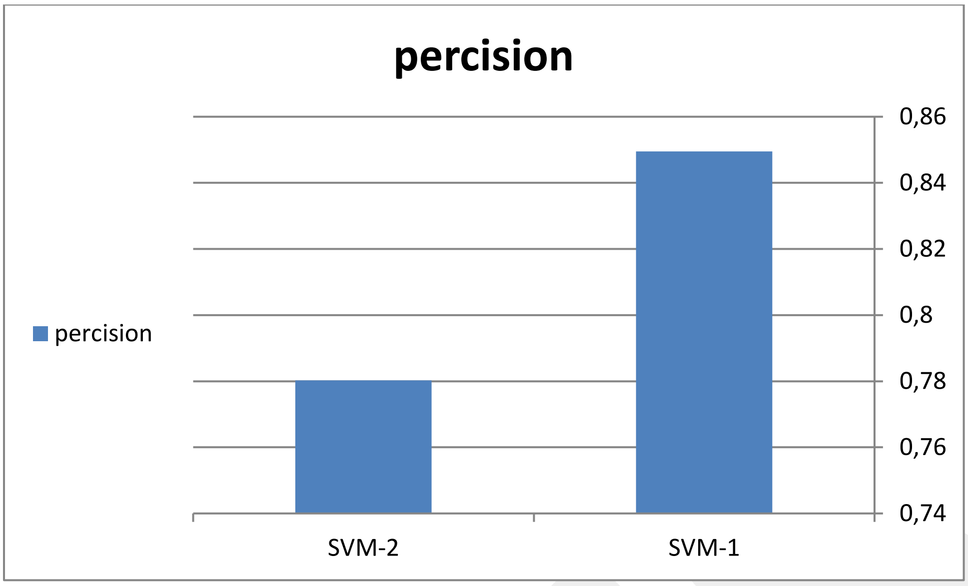


Figure 4.3: Precision results

Precision is also used with recall, the percent of all relevant documents that is returned by the search. The two measures are sometimes used together in the F1 Score (or f-measure) to provide a single measurement for a system.

Note that the meaning and usage of "precision" in the field of information retrieval differs from the definition of accuracy and precision within other branches of science and technology.

Recall

Recall in information retrieval is the fraction of the documents that are relevant to the query that are successfully retrieved. Figure 4.4 shows recall results

$$\text{recall} = \frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{relevant documents}\}|}$$

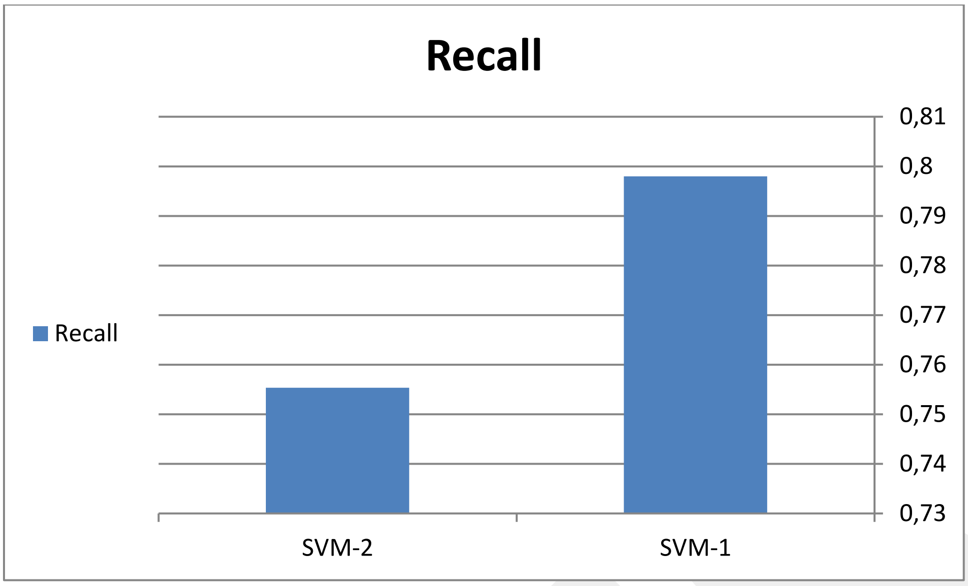


Figure 4.4: Recall results

In binary classification, recall is called sensitivity. So, it can be looked at as the probability that a relevant document is retrieved by the query. It is trivial to achieve recall of 100% by returning all documents in response to any query. Therefore, recall alone is not enough but one needs to measure the number of non-relevant documents also, for example by computing the precision.

Precision and recall are then defined as

$$\text{Precision} = \frac{tp}{tp + fp}$$

$$\text{Recall} = \frac{tp}{tp + fn}$$

Recall in this context is also referred to as the true positive rate or sensitivity, and precision is also referred to as positive predictive value (PPV); other related measures used in classification include true negative rate and accuracy. True negative rate is also called specificity.

$$\text{True negative rate} = \frac{tn}{tn + fp}$$

$$\text{Accuracy} = \frac{tp + tn}{tp + tn + fp + fn}$$

It is possible to interpret precision and recall not as ratios but as probabilities. Precision is the probability that a (randomly selected) retrieved document is relevant. Recall is the probability that a (randomly selected) relevant document is retrieved in a search.

Note that the random selection refers to a uniform distribution over the appropriate pool of documents; i.e. by randomly selected retrieved document, we mean selecting a document from the set of retrieved documents in a random fashion. The random selection should be such that all documents in the set are equally likely to be selected.

In a typical classification system, the probability that a retrieved document is relevant depends on the document. The above interpretation extends to that scenario also (needs explanation).

Another interpretation for precision and recall is as follows. Precision is the average probability of relevant retrieval. Recall is the average probability of complete retrieval. Here we average over multiple retrieval queries.

F-measure

F-measure is a measure that combines precision and recall as the harmonic mean of precision and recall, the traditional F-measure or balanced F-score:

$$F = 2 \cdot \frac{\mathrm{precision} \cdot \mathrm{recall}}{\mathrm{precision} + \mathrm{recall}}$$

This measure is approximately the average of the two when they are close, and is more generally the harmonic mean, which, for the case of two numbers, coincides with the square of the geometric mean divided by the arithmetic mean. There are several reasons that the F-score can be criticized in particular circumstances due to its bias as an evaluation metric.

This is also known as the F1 measure, because recall and precision are evenly weighted. It is a special case of the general F β measure (for non-negative real values of β . Figure 4.5 show F-measure results, and Figure 4.6 show Comparison of SVM-1 and SVM-2 results.

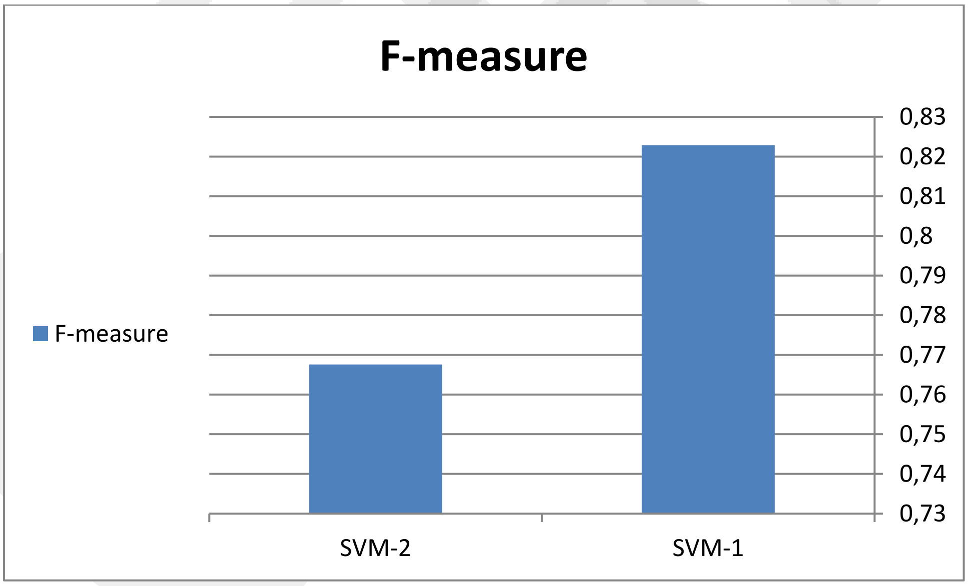


Figure 4.5: F-measure results

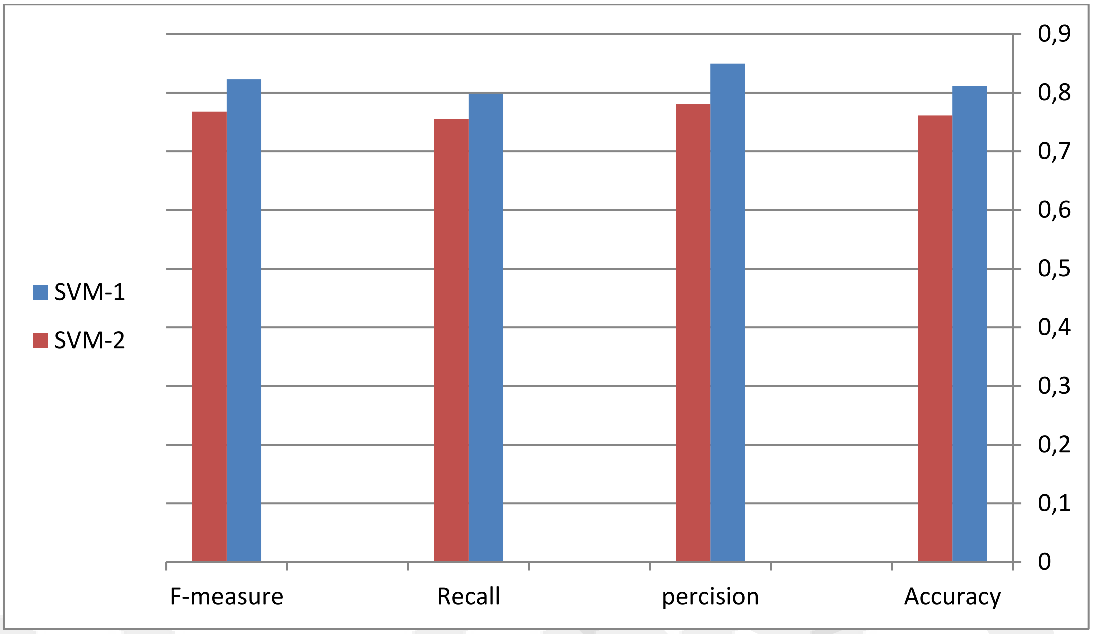


Figure 4.6: Comparison of SVM-1 and SVM-2 results

CHAPTER 5

CONCLUSIONS

In this thesis, we have investigated automatic detection of forbidden objects in x-ray scan images. Specifically, we have worked on detection of forbidden guns. Support vector machine is used as the classifier of the system. Two different features are used for classifications: local binary pattern and histogram of oriented gradients. Images are also pre-processed before feature extraction and classification to improve object detection performance.

Obtained results show that using local binary pattern gives better results than using histogram of oriented gradients for feature.

To support the derived conclusions, the same procedure methods may be applied to other classification algorithms and the effects of other feature extraction algorithms methods on different forbidden objects may be investigated as the future work.

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