Facial Recognition detection Automated Ai Surveillance System

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Abstract— Over the past few years, significant growth in infrastructure has been seen in global security-related issues. Studies such as prevention, detection, and interventions that have led to the development of real-time video monitoring systems are capable of intelligent video processing skills. In short, advanced video-based surveillance can be described as a smart video processing method designed to assist security personnel by providing reliable real-time alerts and supporting well-done video analysis with on-field investigations. Also, it discusses the different types of cameras needed in different natural environments such as indoor and outdoor hire. this has increased the need for security and employment. The rental of videos and photos has become an important area of research. A program based on Intelligent Video Surveillance basically analyzes the performance, performance, or modification of information usually based on people, cars, dogs or something remotely using one of the electronic camera cameras. Different systems are needed to design an effective monitoring system under different lighting conditions. This paper discusses the various requirements for building a robust and reliable video monitoring system.

Keyword- : surveillance based system, digital camera, types of camera, background model, illumination

1 INTRODUCTION

Over the past few decades, the video surveillance market has seen a dramatic change in third-party video surveillance systems, moving to IP video from traditional analog video which has led to improved power performance and the development of algorithm over wifi is the main reason for this change. These Intelligent video monitoring systems are not only limited to laboratories but also reach the market in high demand. With this generation, the era of programs based on Intelligent Video Surveillance began, not only in research labs but also in the market. In early 2010, many research labs, such as Kiwi Security Labs, began broadcasting "Advanced Intelligent Video Surveillance Systems" (IVSS). With the exception of hardware (H / W) and software (S / W) regarded as performance enhancements, or by programming it can be a daunting task to track a person's face and build interoperable performance and system performance depending on system privacy. In addition, in many countries and territories, privacy issues are becoming increasingly important and are considered practical. On the other hand, network performance depends on the performance of each Network Element (NES) system, accessibility, transfer performance, etc., which is considered a decrease in performance and on the other hand, network performance relies heavily on IVS Security System Security and privacy management is also an important part of implementation security measures and security management forms and appropriately in the operation of the system such as reducing homicides. From the point of view of the Security Management System, the development of the proposed science process was the driving force of building an ongoing IVS elite, using a robust System Management System, which controls system implementation, i.e., system accessibility.

2 OBJECTIVE

Advanced video-based surveillance system could be described as an intelligent video processing technique designed to assist security personnel by providing reliable real-time alerts and to support efficient video analysis for forensic investigations.

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3. RELATED WORK

The results presented here are based on two basic methods: multilayer perceptron (MLP), and learning vector quantization (LVQ). In both cases, two types of data were assigned to separators: reduced resolution images (gray or split level), and feature vectors. The first method used was based on MLP. Other experiments were performed using the topology of two hidden layers with 674, 76, 16 and 20 input neurons, two hidden and outgoing layers, respectively. One experiment used MLP with only one layer of secretion, with a localization of 675, 101 and 20 neurons of the insertion, hidden and output layers. The second method used was LVQ (learning vector quantization, [6]). This method works as a 1-NN separator that differs in how a set of label patterns are formed: this set is usually obtained by combining data (reducing the number of labeled patterns), and using a supervised learning algorithm to move cluster centers into positions that minimize segmentation error. Most codebooks are usually provided with vectors in each class, and each test pattern is given to the class with the nearest vector codebook. One, two or three codes per class are used here. For geometric features, two identical methods (MLP and LVQ) have been tested. for Each of them is nourished by a number of different features, given the expansion of Karhunen-Loeve. For MLP, Table I shows that the number of neurons in the input layer has been (equal to the number of selected elements) and the number of neurons in the hidden layer. The number of neurons in the extraction layer remains at 30. In the LVQ, the carrying of one, two or three codes per class was considered for 5, 10 and 15 factors.

4 METHODOLOGY

In this section we will discuss the methodology that we are using to avoid accidents block diagram of the proposed system is shown below

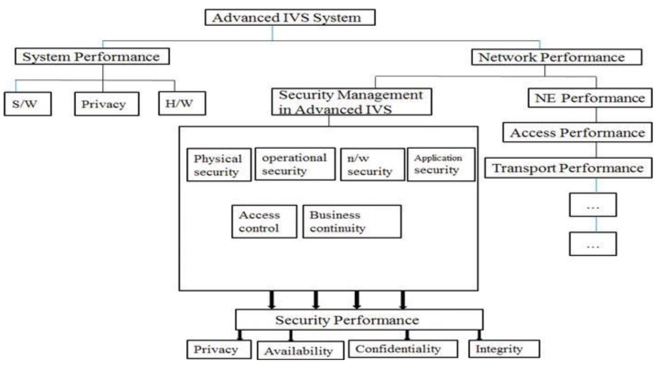

Figure 1: Block diagram of our proposed system

4.1 Algorithms used

4.1.1 Object Detection

Data flows through CNN layers and various operations are performed on data. The Learning rates ,number of epochs and batch size are defined. Training accuracy and training losses are constantly monitored. Confusion matrix is then plotted using training and testing data. Various performance parameters can be defined and observed using the confusion matrix.this will help in find the data flow

4.1.2 Neural Network Training

First step in training a network using deep learning for an application is to prepare an appropriate dataset and make a Train-Test Split depending on the available data. Suitable network is designed or selected for training.Model with best validation loss is saved and tested on real world dataset. The model is said to be good if a decent precision and recall values are obtained for new datasets, else the model is trained on enhanced datasets for boosting the performance.

4.1.3 Multiple Object Detection

An image is given as the input to the algorithm and transformation is done using CNN. Flattening is converting data into a 1-dimensional array for inputting it to next layer. Object detection pipeline has one component for generating proposals for classification. As the proposal generation method should have high recall, we keep loose constraints in this stage. However, processing these many proposals all through the classification network is cumbersome. This leads to a technique, which filters proposals based on some criteria called Non-Maximum Suppression. IOU calculation is actually used to measure the overlap between two proposals.

4.1.4 Multiple Object Tracking

In multiple object tracking We train the tracker using YOLOv3 and deep learning methods and optimize the detector's success rate by providing efficient detection results. It consists of six phases such as loading data set, YOLOv3 design, training options configuration, object tracker training, and tracker evaluation, respectively.

4.1.5 Face Detection Algorithm

A Haar-like feature considers adjacent rectangular regions at a specific location in a detection window The difference in pixel densities is then used to categorize subsections of an image, like the eye region in a face image that is part of a training image database containing human faces. To detect a face with a very good accuracy, a large number of Haar-like features are organized in a cascade to form a strong classifier. The search window is moved across the entire input image at multiple locations and at multiple scales. For each sub-section of the image, the Haar cascade is applied.

5. SYSTEM HARDWARE AND SOFTWARE CONFIGURATION

5.1 Hardware Components

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5.1.1 Camera with Night vision

Active night vision based systems involve a camera and a bright light that emits infrared radiation (which happens to be invisible to the naked eye). The camera is sensitive to this light and picks it up. Passive night vision based systems use an image intensifier tube to amplify existing light and gives a better picture at night

Figure 2: Digital Camera Night Vision CCTV Camera

5.1.2 IR Scanner

An IR Scanner is a specialized thermography tool for infrared energy detection. The non-contact device detects infrared energy (heat) and converts it into an electronic signal, which is then processed to produce a thermal image on a touchscreen monitor and to perform temperature calculations in case any movement will activate the system in return reducing the load on the servers .

Figure 3: IR Scanners

5.1.3 Buzzers

Figure 4: Buzzer Alert 2V to 28VDC, 93db surface mount

A buzzer is an audio signal device, which may be mechanical, electromechanical. It is used as an alarm device when an unauthorised person enters. to alert if there is any kind of suspicious movements in the camera

5.1.4 IR sensors

Infrared sensor emits in order to sense some aspects of the surroundings. It is capable of measuring heat of an object as well as can detect the motion. These types of sensors can only measure infrared radiation, instead of emitting it that is called as a passive IR sensor. they are attached to the camera

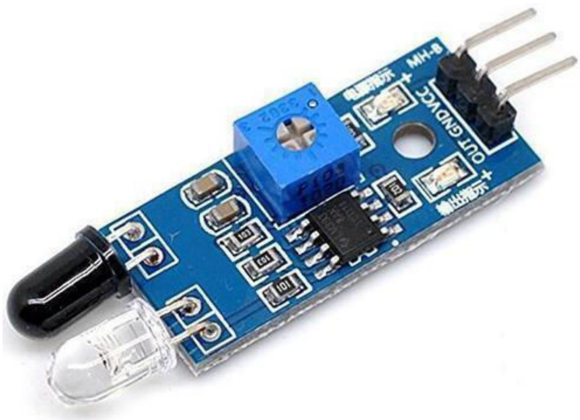

Figure 5: IR Sensor

5.2 Software configuration

In the proposed system there are some necessary software tools required for the system. They are Jupyter notebook, Packages like numpy,pandas,twilio,fastap,DLib,cmake and icecream ; mongoDb Database; TenserFlow and OpenCv library.

6. EXPERIMENTAL RESULTS

Test results are summarized in Tables 2 to 4. Table 2 shows the percentage of correct recognition obtained with gray-scale measurement images and MLP (for 674, 75, 15 and 30 neurons input, two hidden and outgoing layers), or LVQ (with one, two or three codecs). in each class). The images were reduced to versions of the original image resolution, including the previous and round views, and were calculated with gaussian estimates and sample shrinkage. In some experiments, these rough images have become standard or fragmented.

Table 2. Percentage of successful recognition for gray level images

Input image	MLP 2 hidden layers	LVQ 1 codevector per class	LVQ 2 codevectors per class	LVQ 3 codevectors per class
Gauss (frontal)	43.3	96.6	96.6	96.6
Gauss (rotated)	26.6	83.3	96.6	96.6
Normalized (frontal)	83.3	93.3	96.6	96.6
Normalized (rotated)	80.0	90.0	93.3	93.3
Gauss & Segment.	None	40.0	40.0	40.0

other experiments were also completed to compare the performance of the MLP model method when using one or two hidden layers. For that purpose, MLP with 1000 neurons in the hidden layer was tested. Effects of reduced video resolution, abnormal images summarized in table 3.

Table 3. Percentage of successful recognition for different MLP topologies

	MLP (one hidden layer)	MLP (two hidden layers)	LVQ (two codevectors per class)
Gauss	73.3%	43.0%	96.0%

Table 4 outlines the main results achieved for the geometrical features case. Like in Table 2, the results have been produced by MLP (with one hidden layer, in this case) and LVQ (with one, two or three code vectors per class). Figure 6 depicts the evolutions of the success rates when the number of provided features is increased

Table 4. Percentage of successful recognition for geometrical characteristics

Number of features provided by KL	MLP	LVQ (1 codevector per class)	LVQ (2 codevectors per class)	LVQ (3 codevectors per class)
5	44.4	36.3	45.5	40.0
10	84.8	77.0	78.5	77.7
15	93.3	83.7	81.8	84.4

A logical quote from Tables 2 to 4 shows that, in the analysis of images at the gray and video scale level, better results were obtained with LVQ than MLP. This result was inconsistent with the previous or rotated view, with no additional image editing categories (customization or segmentation). Further, Table 2indicates that the methods (in particular, LVQ) were robust systems for small or medium-sized head exchanges, and that altering the gray levels of images by the process of its separation adversely affected the results of the methods. This may be due to the gray matter details lost in the separation process or to the erroneous effect of the separation you have on such a decision. In the case of geometric features, the situation is reversed: the MLP model (with one hidden layer) achieved higher success rates than the LVQ. With regard to the topology of the MLP model, positive results were obtained with only one hidden layer rather than two (another advantage of using only one hidden layer with reduced training times) In any case, LVQ with gray images and video proved to be the best method tested here, including in the middle an LVQ with geometric features. This effect is similar to that of Brunelli [2], perhaps because gray-colored images contain more detail than geometric features. It should be noted that the automatic or manual presentation of the points resulted in similar results (90% for Brunelli [2] and 93.3 and 84.4% for us).

7. CONCLUSION

Key points for the Advance Intelligent Surveillance system (IVSS) are creating a viewing system that can act as an internal / internal viewing system. The Advanced Intelligent Video Surveillance System has a variety of recording capabilities. At present safety and security take up an important part of human life. A good viewing engineer will have the following features: elite flexibility, easy upgrades, low upgrade costs, and cost-cutting movements as the app starts with volume trends. Also, step-by-step design performance limits the functionality of the Monitoring system, so the level of security must be increased for the specific purpose of preventing the intervention of mediators. Currently, the video surveillance industry is using simple CCTV cameras and communication channels as the basis for viewing programs. These parts of the program are not easily expandable and have low video resolution with 0 flag correction. However, future and future video surveillance programs will take over these things with computer-enabled LAN cameras now, complex image management, and video-

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over-IP guidance. They will no longer have surveillance camera systems but this has been added to video communication systems.

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