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Enhancing Automotive Security: Biometric Authentication for Vehicle Access Control

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ABSTRACT

Enhancement in vehicle technology system is getting increased research popularity and adding a vehicle theft security system in order to avoid getting vehicle theft in the parking and sometimes driving in unsecured places. The proposed system provided security and better theft control by using facial recognition and vein authentication , when the unauthorized person try to . The system uses deep learning models and bilateral filtering to improve the detection accuracy. The proposed system is very simple with greater security for vehicle anti-theft protection and low cost technique compared to others.

Keywords: Vein Pattern Recognition, User Authentication, Vehicle Access Authorization

INTRODUCTION

Motor vehicle theft

Motor vehicle theft (also known as a car theft and, in the United States, grand theft auto) is the criminal act of stealing or attempting to steal a motor vehicle. Nationwide in the United States in 2020, there were 810,400 vehicles reported stolen, up from 724,872 in 2019.[1] Property losses due to motor vehicle theft in 2020 were estimated at $7.4 billion. There were 505,100 car thefts in the EU in 2019, a 43% decrease from 2008.[2]

Methods

Some methods used by criminals to steal motor vehicles:

Theft of an unattended vehicle without a key: the removal of a parked vehicle either by breaking and entry, followed by hotwiring or other tampering methods to start the vehicle, or else towing. In London, the police say that 50% of the annual 20,000 car thefts are now from high-tech OBD (Onboard Diagnostic Port) key-cloning kits (available online) and bypass immobilizer simulators. Taking without owner's consent (TWOC): the unauthorized use of a car short of theft. This term is used in the United Kingdom, as is the derivative "twocking"

Opportunistic theft: either the removal of a vehicle that is unattended with the keys visible and sometimes the engine idling, or theft of a vehicle offered for sale during what thethief represents as a test drive. A "test drive" may also give a potential thief insight into where the vehicle keys are stored, so that the thief may return later to steal the vehicle.

Carjacking: taking a vehicle by force, or threat of force, against its owner or operator. In most places, this is the most serious form of vehicle theft, because assault also occurs and the method of taking over the vehicle is essentially a robbery, a more serious form of theft.In some carjackings, the

operators and passengers are forced from the vehicle while the thiefis driving it. In other incidents, the operator and/or passenger(s) are held hostage in it. In still others, which are less common, the assailant forces the lawful operator to drive in accordance with the demands of the assailant, who rides as a passenger.[3]

Fraudulent theft: illegal acquisition of a vehicle from a seller through fraudulent transfer of funds that the seller will ultimately not receive (such as by identity theft or counterfeiting a cashier's check), or through the use of a loan obtained under false pretenses. Many vehicles stolen via fraud are soon resold, by the thieves. Using this approach, the thief can quietly evade detection and continue stealing vehicles in different jurisdictions. Car rental companies and car dealerships are also defrauded by car thieves into renting, selling, financing, or leasing them cars with fake identification, checks, and credit cards. This is a common practice near national borders, where tracking devices are less effective because the victims may lack jurisdiction in the countries into which the vehicles quickly are removed.

Frosting: Occurring in winter, which involves an opportunist thief stealing a vehicle with its engine running whilst the owner de-ices it.

"Hanoi burglary", where a vehicle is taken during a house burglary, often done with the explicit purpose of obtaining car keys.[4] Named after the first police operation targeting the method.[4]

Joyriding: refers to driving or riding in a stolen vehicle, most commonly a car, with noparticular goal other than the pleasure or thrill of doing so.

Keyless system theft: The risk of cars with keyless entry being stolen is high. These are cars where the owner does not have to even press a button to unlock as long as the key is located at a certain distance from the vehicle. In theory, the key's signal should no longer reach the car when the driver moves away, making it impossible to unlock the car. Car thieves extend the signal from the owner's key with the help of simple signal amplifiers. and then all they have to do is open the door, hit the start button and drive away unnoticed. The car's alarm system is totally blind to this.[5]

LITERATURE SURVEY

P. V. Crisgar, P et al propose a Vehicle Tracking System to find vehicle coordinates. We implement vehicle movement detection and vehicle engine monitoring, which indicates an act of theft. Data and telemetry are sent over the Internet via cellular networks, while location detection relies on a GPS module with an external Antenna. Data is sent via the MQTT Protocol via Google Cloud IoT Core, which will be sent to the Firestore Database available from Google Firebase. The data can be monitored by the vehicle owner via a Progressive Web App-based User Interface, also built on top of Firebase, which will be able to control device mode, display the real-time location of the vehicle via Google Maps, and a collection of historical data on vehicle movements. The system will alert the user via notification when an act of theft is detected.

S. Shammi, et al presents an automated way of detecting vehicle theft as it happens. This procedure is based on moving object detection using Canny Edge Detection method and eventually notifying the security personnel or the parking lot operator about the movement. The first step is to detect the edges through Canny method and then finding the edge change ratio to finally determine a movement. Canny is one of the modern Edge detection techniques and choosing this one over other methods is because of the double thresholding and its better performance, which makes the method described in this paper efficient and useful. This paper proves the effectiveness of the described method.

K. Chandra Prabha et al proposes a framework that utilizes the blend of methods like face recognition and detection using Neural Network.The face recognition is performed on live images with no application field as a primary concern and it refers to the mental cycle process by which people find and take care of appearances in a visual scene. Processes used in the framework are white balance rectification, skin like district segmentation, facialcomponent extraction and face image extraction on a candidate‟s face. At that time, a face arrangement technique is utilized the Feedforward Neural Network to coordinate the
framework. Framework is additionally equipped for identifying and perceiving different faces in live gained security framework for vehicle.

C. Krishnaprasad et al proposes a theft detection system capable of identifying fuel theft, ignition tampering, and vehicle lifting in two-wheelers. The system has GPS/GSM capabilities for real-time location tracking and SMS alerts. An old/unused android smartphone is installed inside the vehicle for providing these capabilities. It reduces the cost and carbon footprint of the system. Vehicle tampering is detected using a piezoelectric vibration sensor. An Atmega328 MCU is used to monitor the vibration sensor and the inbuilt fuel level sensor of the vehicle. The MCU can also control the alarm and the ignition system of the vehicle using relays. Two android applications are developed for the system. The first application acts as an interface between the MCU and the phone installed inside the vehicle. The phone generates SMS alerts and sends updates to an online database in response to the alert signals generated by the MCU. All theft reports are stored in a Google Firebase database. The second application is installed inside the user's phone. It allows the user to lock/unlock and track the vehicle. Finally, the system includes a user forum where users can post theft reports from the database and interact with other users of the application.

A. Jayakody, et al presents the design, implementation and testing of the prototype model that has been built as the proposed solution to prevent or minimize vehicle parts theft and detect the authenticity of the vehicle parts, if original parts of the vehicle were replaced with aftermarket parts without the user's consent. Theft and authenticity of vehicle parts are detected using RFID technology in the developed prototype model. To make this vehicle security system an affordable solution to the vehicle owners, a single low-cost RFID readeris used and an anti-collision mechanism is built based on TDM and signal relaying, as a cost cutting strategy to read multiple RFID tags.

EXISTING SYSTEM

Automatic image segmentation techniques can be classified into four categories, namely, (1) Clustering Methods, (2) Thresholding Methods, (3) Edge-Detection Methods, and (4) Region-Based Methods [6].

Clustering Methods

Clustering is a process whereby a data set (pixels) is replaced by cluster; pixels may belong together because of the same color, texture etc. There are two natural algorithms for clustering: divisive clustering and agglomerative clustering. The difficulty in using either of the methods directly is that there are lots of pixels in an image. Also, the methods are not explicit about the objective function that is being optimized. An alternative approach is to write down an objective function and then build an algorithm. The K-means algorithm is an iterative technique that is used to partition an image into K clusters, where each pixel in the image is assigned to the cluster that minimizes the variance between the pixel and the clustercenter and is based on pixel color, intensity, texture, and location, or a weighted

combinationof these factors. This algorithm is guaranteed to converge, but it may not return the optimal solution. The quality of the solution depends on the initial set of clusters and the value of K .

Thresholding Methods

Thresholding is the operation of converting a multilevel image into a binary image i.e., it assigns the value of 0 (background) or 1 (objects or foreground) to each pixel of an image based on a comparison with some threshold value T (intensity or color value). WhenT is constant, the approach is called global thresholding; otherwise, it is called local thresholding. Global thresholding methods can fail when the background illumination is uneven. Multiple thresholds are used to compensate for uneven illumination. Threshold selection is typically done interactively.

Convolutional Neural Network (CNN)

This network structure was initially proposed by Fukushima in 1988 . It was not widely used; however, it is used due to the limits of computation hardware for training the network. In 1990s, LeCun et al. applied a gradient-based learning algorithm to CNNs and attained successful results for the handwritten digit classification problem.

Subsequently, scholars further upgraded CNNs and reported state-of-the-art results in many recognition tasks. CNN's have numerous advantages over DNNs. The most important one is being more like the human visual processing system, being highly optimized in the structure for processing 2D and 3D images, and being effective at learning and extracting abstractions of 2D features. The max-pooling layer is very effective in absorbing shape variations. Likewise, it is also composed of meagre connections with tied weights. When compared to a fully connected network of similar size, CNNs have considerably fewer parameters. Almost all CNNs are skilled with the gradient-based learning algorithm and it suffers not as much from the diminishing gradient problem. CNN can yield highly optimized weights when the gradient-based algorithm trains the whole network to decrease an error criterion directly. Figure 9 displays the overall architecture of CNNs. It comprises two main parts: They are feature extractors and a classifier.

Each layer of the network accepts the output from its close previous layer as its input in the feature extraction layers. Similarly, it passes its output as the input to the subsequent layer. The CNN architecture comprises a blend of three types of layers: Convolution, max-pooling,and classification. The low and middle-level of the network involves two types of layers. They are Convolutional layers and max-pooling layers. The even-numbered layers are intended for convolutions and the odd-numbered layers are intended for max-pooling operations. The output nodes of the convolution and max-pooling layers are clustered into a 2D plane named feature mapping. The combination of one or more planes of preceding layers usually derives each plane of a layer. The nodes of a plane are attached to a small region of each connected planes of the preceding layer. The features from the input images by convolution operations on the input nodes are extracted from each node of the convolutional layer.

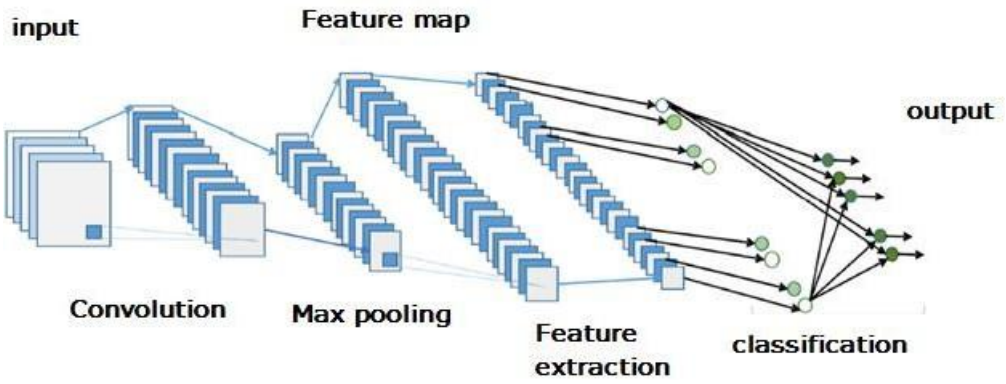


Figure: The overall architecture of the Convolutional Neural Network (CNN) comprisesan input layer, multiple alternating convolution and max-pooling layers, one fully-connectedlayer and one classification layer.

The features propagated from lower-level layers derive higher-level features. Depending on the size of the kernel, the dimensions of features are reduced for the convolutional and max-pooling operations respectively when the features propagate to the highest layer or level. Though in order to represent better features of the input images for ensuring classification accuracy, the number of feature maps is usually increased. The fully connected network is also known as the classification layer. The output of the former layerof the CNN is used as the input for this fully connected network. Because of the better performance, the feed-forward neural networks have been used as the classification layer. With respect to the dimension of the weight matrix of the final neural network, the extracted features are taken as inputs in the classification layer. On the other hand, the fully connected layers are costly in terms of network or learning parameters. Average pooling and global average pooling are some of the new techniques emerged in recent years. These techniques can be used as an alternative to fully-connected networks. It uses a soft-max layer for the calculation of the score of the respective class in the top classification layer. The classifier provides output for the corresponding classes, based on the highest score. The succeeding section discusses the mathematical details on different layers of CNNs.

Convolutional Layer

The feature maps from previous layers are convolved with learnable kernels, in this layer. In order to form the output feature maps, the output kernel goes through a linear or non-linear activation function, such as sigmoid, hyperbolic tangent, Softmax, rectified linear,and identity functions). Each one of the output feature maps can be united with more than one input feature map. In general, it can be expressed as:

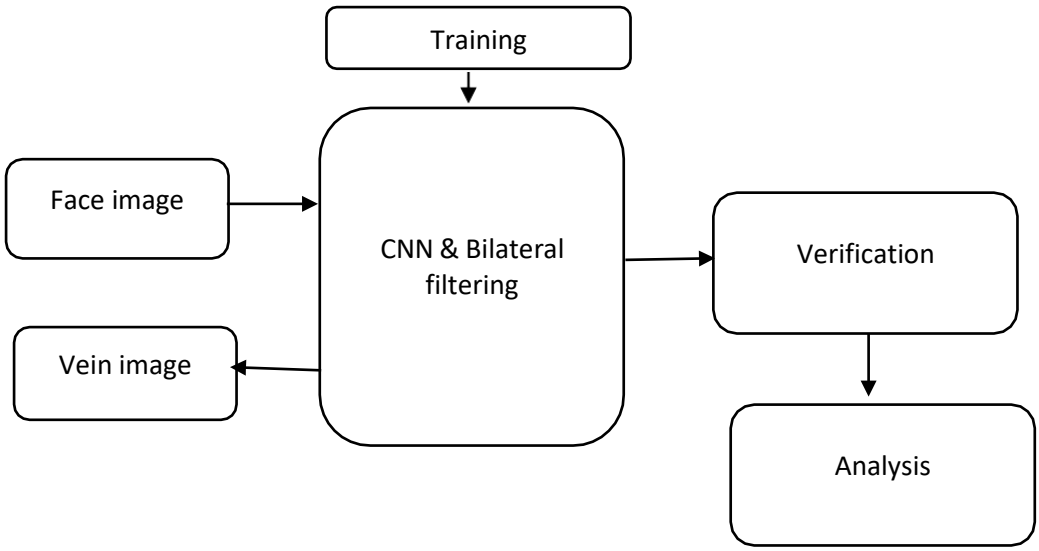
$$x_j^l = f\left(\sum_{i \epsilon M_j} x_i^{l-1} * k_{ij}^l + b_j^l\right),$$

Where xjl denotes the output of the current layer, xil-1 denotes the previous layer output, kijldenotes the kernel for the present layer, and bjl denotes the biases for the current layer. mj signifies a selection of input maps. An additive bias b is given for each output map. However, the input maps will be convolved with unique kernels to produce the corresponding output maps. The output maps finally go

through a linear or non-linear activation function (such as sigmoid, hyperbolic tangent, Softmax, rectified linear, or identity functions).

PROPOSED SYSTEM

This is an advanced system which can be utilized in many cars our system uses facial recognition to identify the authorized users of the vehicles and only authorized users allowed to use the vehicle. In this system we are designing facial recognition algorithm which will identify the driving person based on which the vehicle ignition can be controlled. Further vein authorisation provided for two level security.



Face imagesafter grayscale conversion Non-Face imagesafter grayscaleconversion

Figure:4.2

Computing Integral Image:

Rectangular features can be computed rapidly using Integral images. An integral imageat location (x,y) is calculated using the sum of the pixels above and to the left of x, y, inclusive.

The image below depicts the calculation for an integral image.

	x_0	x_1	x_2	x_3
y_0	1	12	45	10
y_1	6	5	11	4
y_2	3	7	10	8
y_3	5	9	4	7

Original Image (Grayscale)

$$ii(x,y) = \sum_{x' \leqslant x,\, y' \leqslant y} i(x',y')$$

i – original image
ii – integral image

	x_0	x_1	x_2	x_3
y_0	1	13	58	68
y_1	7	24	80	94
y_2	10	34	100	122
y_3	15	48	118	147

Integral Image

Using the Integral image, any rectangular sum can be computed using four array references. Since the process of extracting haar-like features involves computation of the rectangular sum of lighter/darker regions, the introduction of Integral images greatly speeds up the process. We have computed integral images for our entire dataset. We then proceeded to build our Haar-like features.

- **Extracting Haar Features:**

Viola and Jones in their paper has defined the following **3 types of Haar-like features** as follows:-

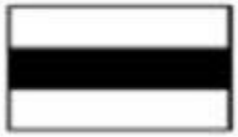
- **Edge features**

- **Line feature**

- **Four-sided feature**

In addition to the above four features, we have considered **a fifth feature of type Linefeature** in our project as follows:-

- **Fifth line feature**



In the code, we have created a dictionary for the above five types of Haar-like features which stores tuples denoting our individual Haar features:-

Viola-Jones Algorithm:

Viola-Jones algorithm had used a variant of AdaBoost for training. We have used thefollowing steps in our algorithm:

- Initialized weights for each training example Normalized all the weights
- Then we selected the best weak classifier based on the weighted error of the trainingexamples
- Then updated the weights according to the error of the chosen best weak classifier
- Repeated steps 2–4 N times, where N is the desired number of weak classifiers

A detailed description of the steps implemented are as follows:

- **Initialized weights for each training example**

At the start of the algorithm, we gave each training example the same weight. If the positive classes are p in number and negative classes are n in number, then we have assigned the following weights to the training examples:

$$w_i = \begin{cases} \frac{1}{2p} & \text{if } x = 1, \\ \frac{1}{2n} & \text{if } x = 0 \end{cases}$$

Where **x** is the class of the training example.

Basic CNN Architecture

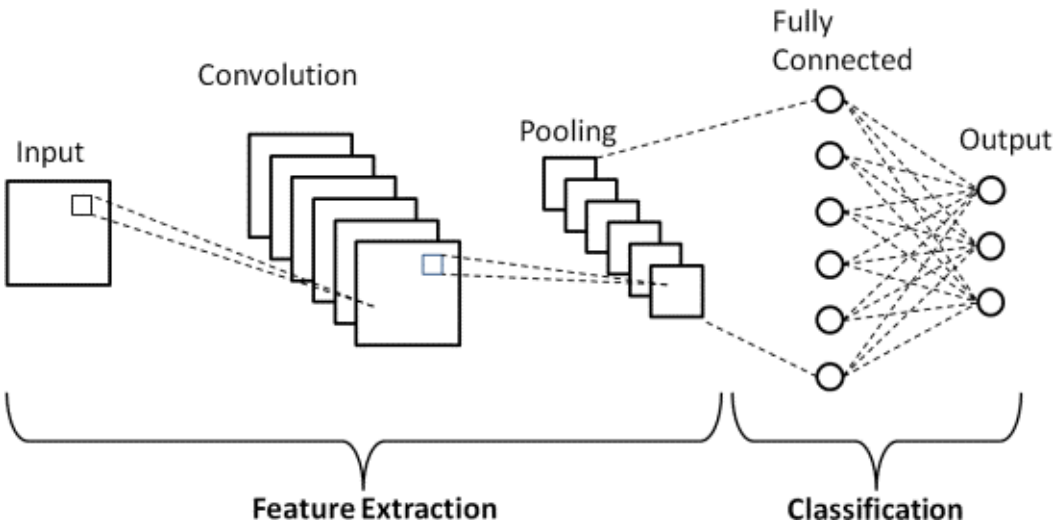


Figure:4.3 CNN architecture

ALGORITHM FOR VEIN RECOGNTION

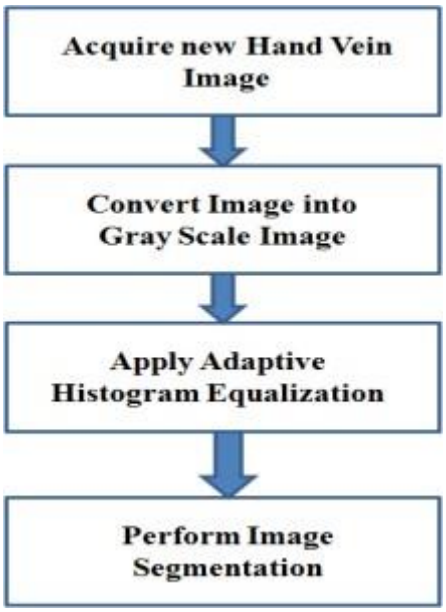


image work flow

The algorithm of the image processing is as shown above And the details of each step is as follows 2 IMAGE ACQUISTION Fig shows the example of captured vein images using proposed system. The software used for pre-processing is MATLAB 2009 of version 7.9.0

Example of vein image captured by proposed system

Adaptive histogram equalization works by considering only small regions and based on their local cdf, performs contrast enhancement of those regions. CLAHE operates on small regions in the image, called tiles, rather than the entire image. Each tile's contrast is enhanced, so that the histogram of the output region approximately matches the histogram specified by the 'Distribution' parameter. The neighboring tiles are then combined using bilinear interpolation to eliminate artificially induced boundaries. The contrast, especially in homogeneous areas, can be limited to avoid amplifying any noise that might be present inthe image. Figure 4 shows the image after applying CLAHE to the image.

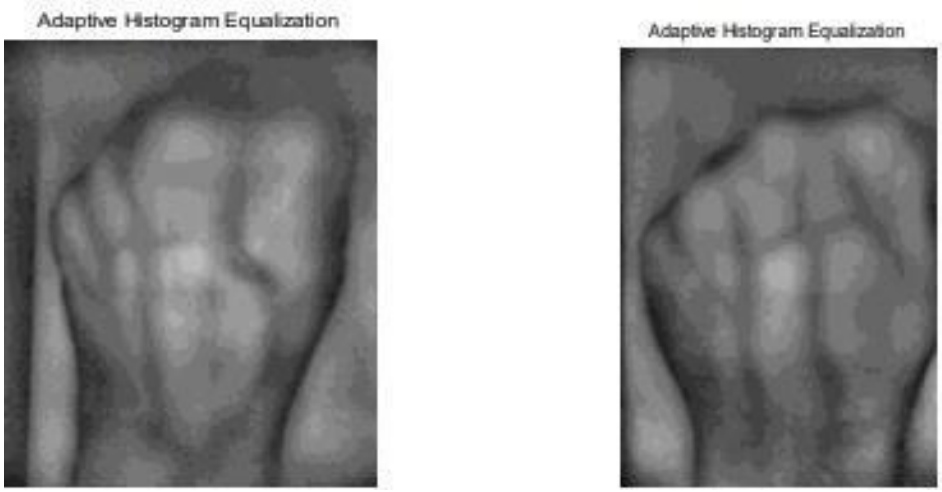
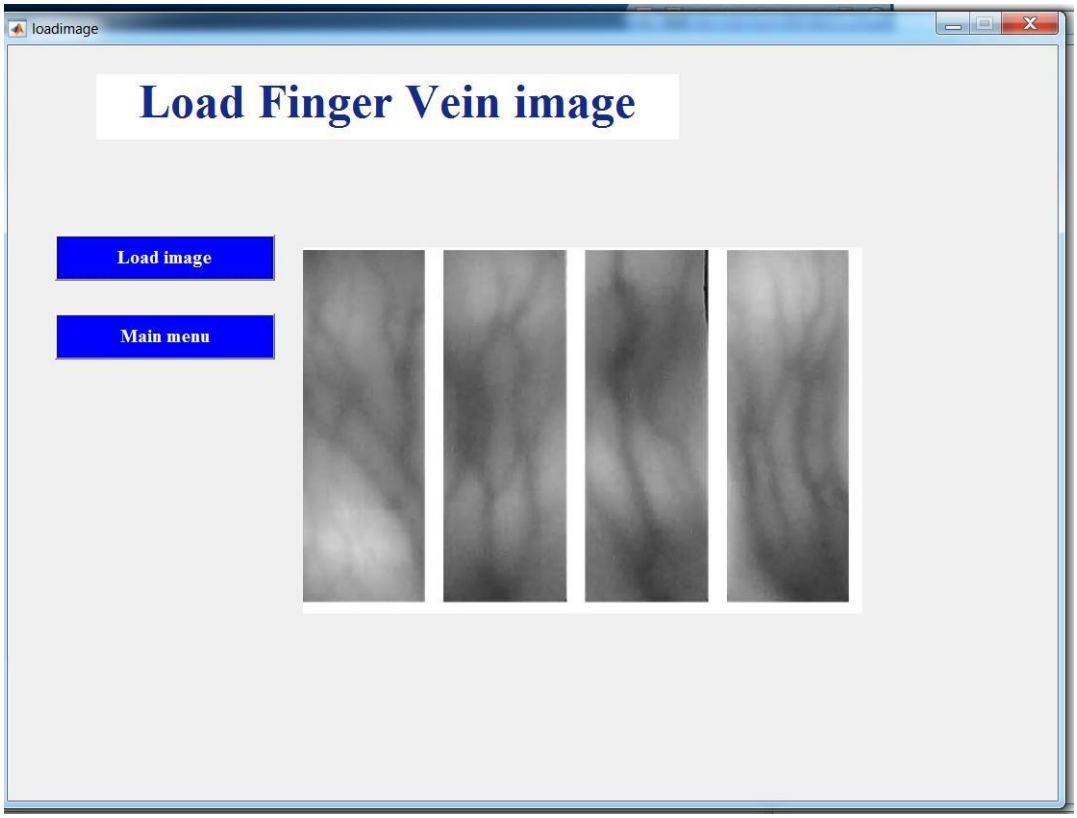
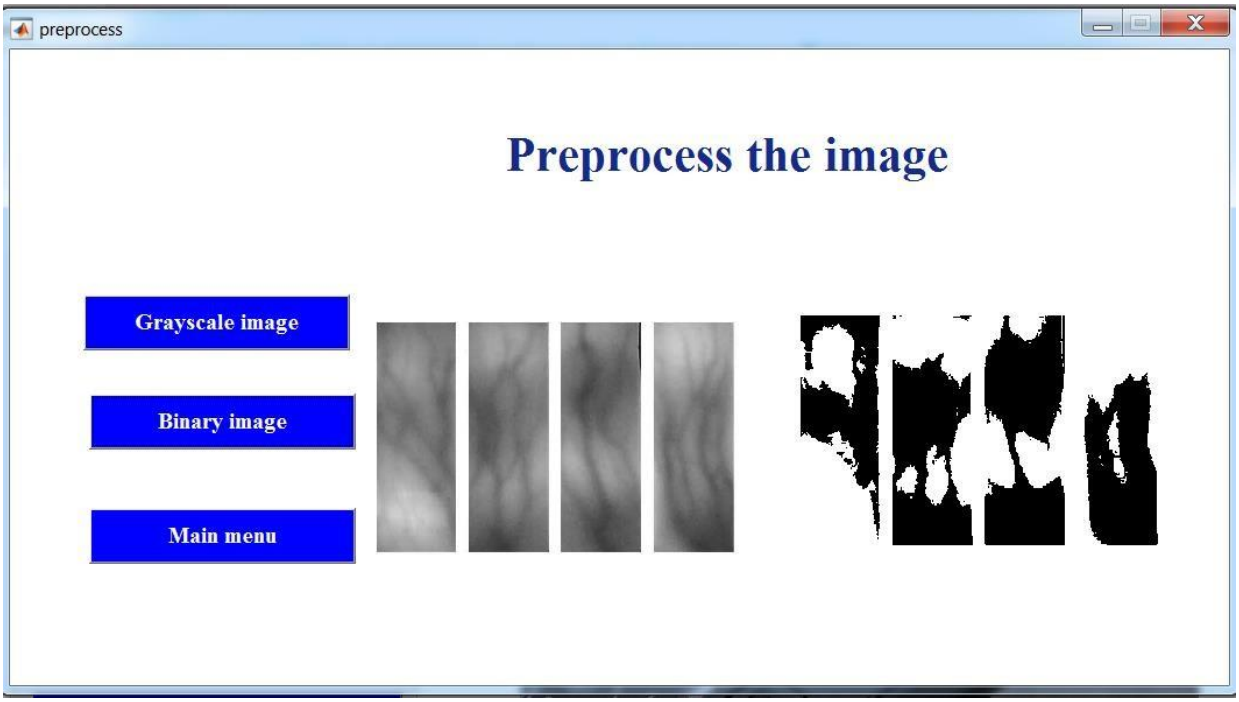
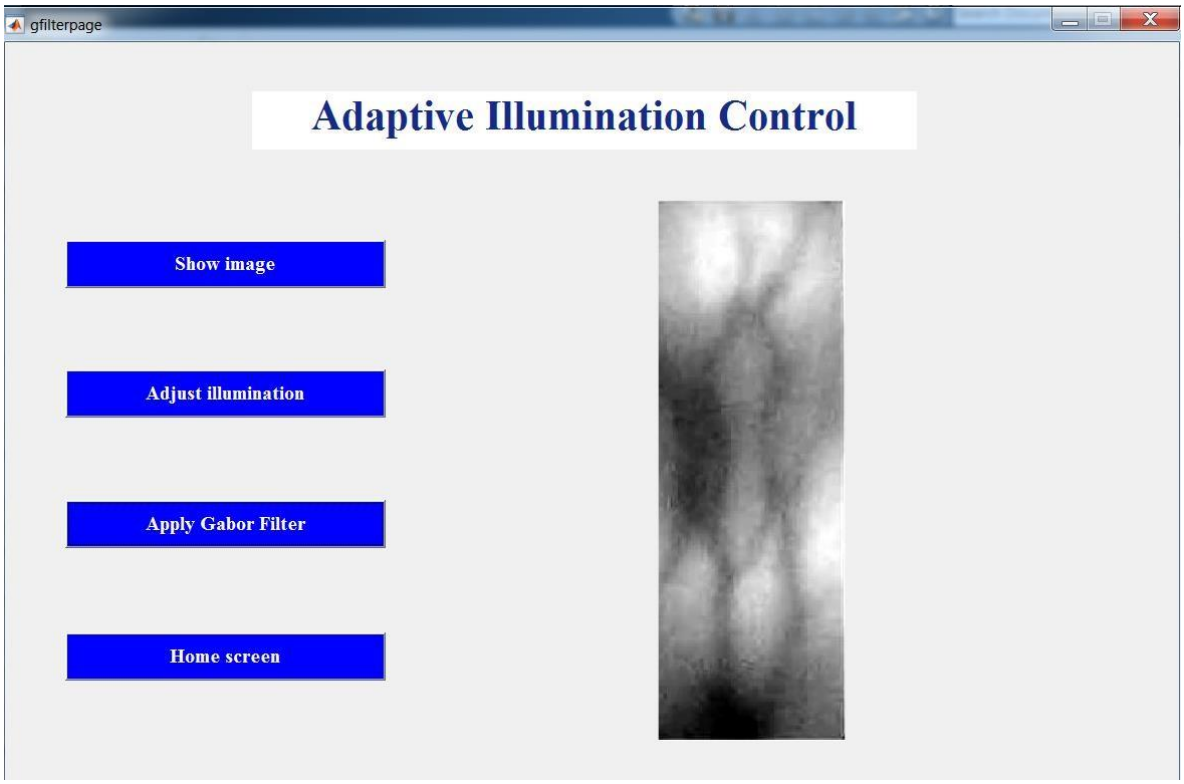


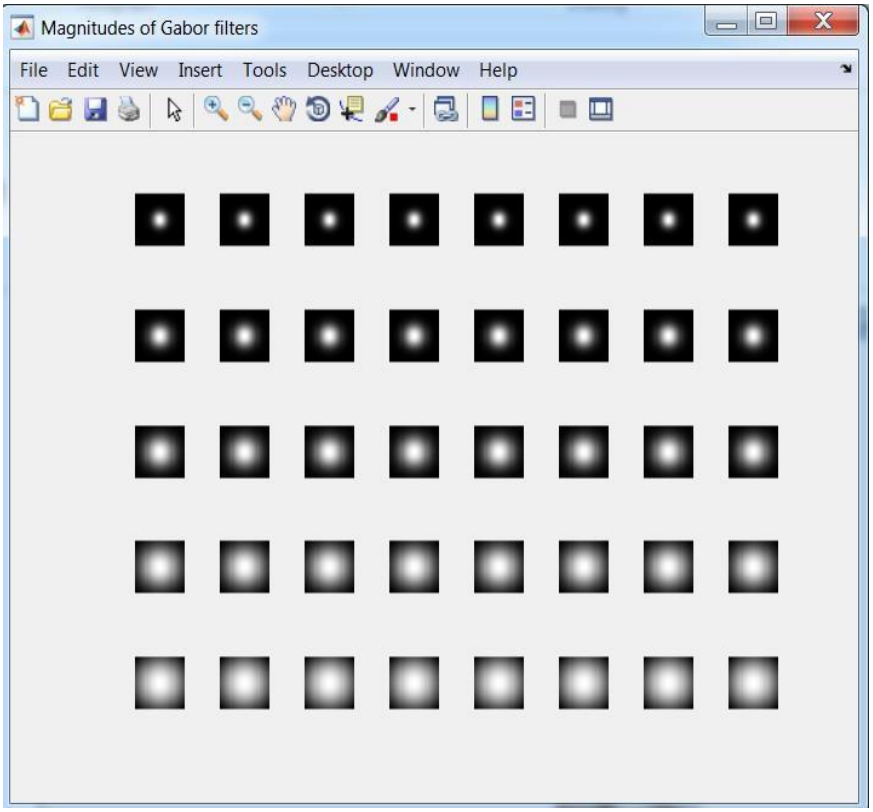
Figure: Images After Applying CLAHE

RESULT & DISCUSSION

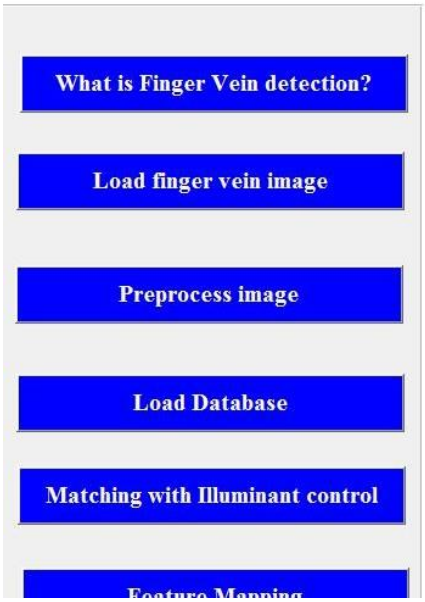


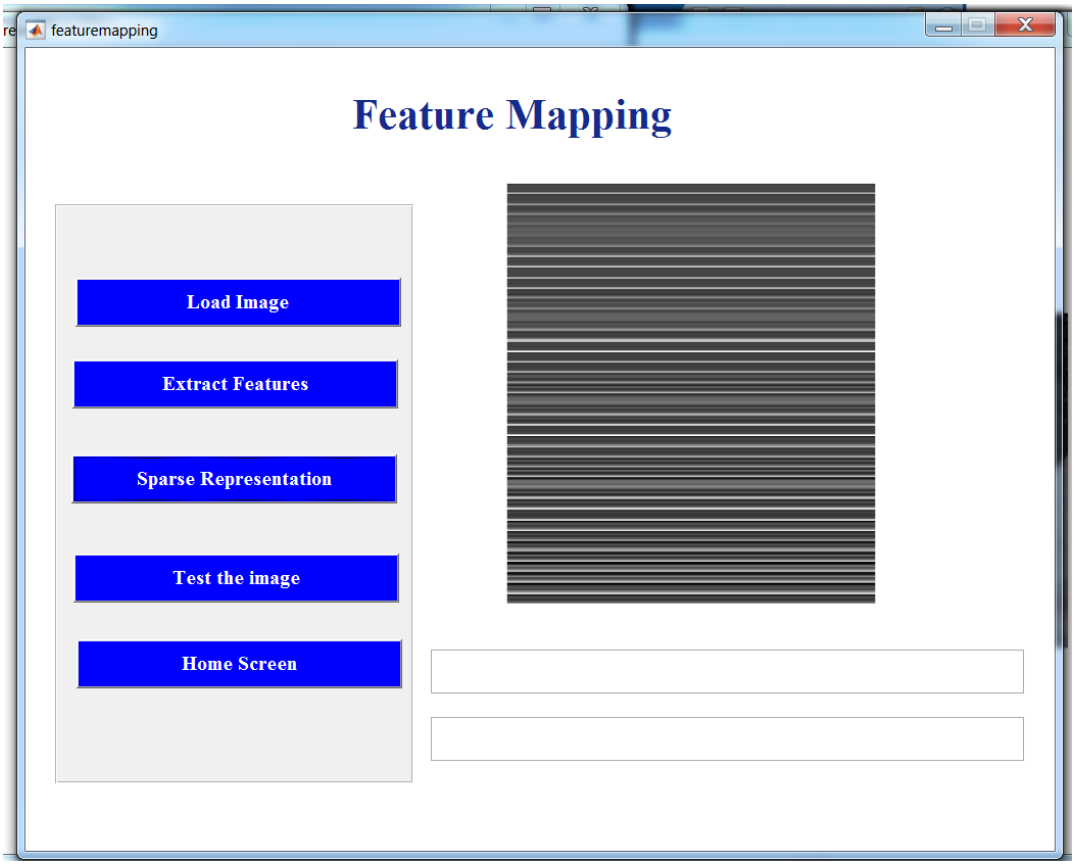

preprocess
Preprocess the image
Grayscale image
Binary image
Main menu

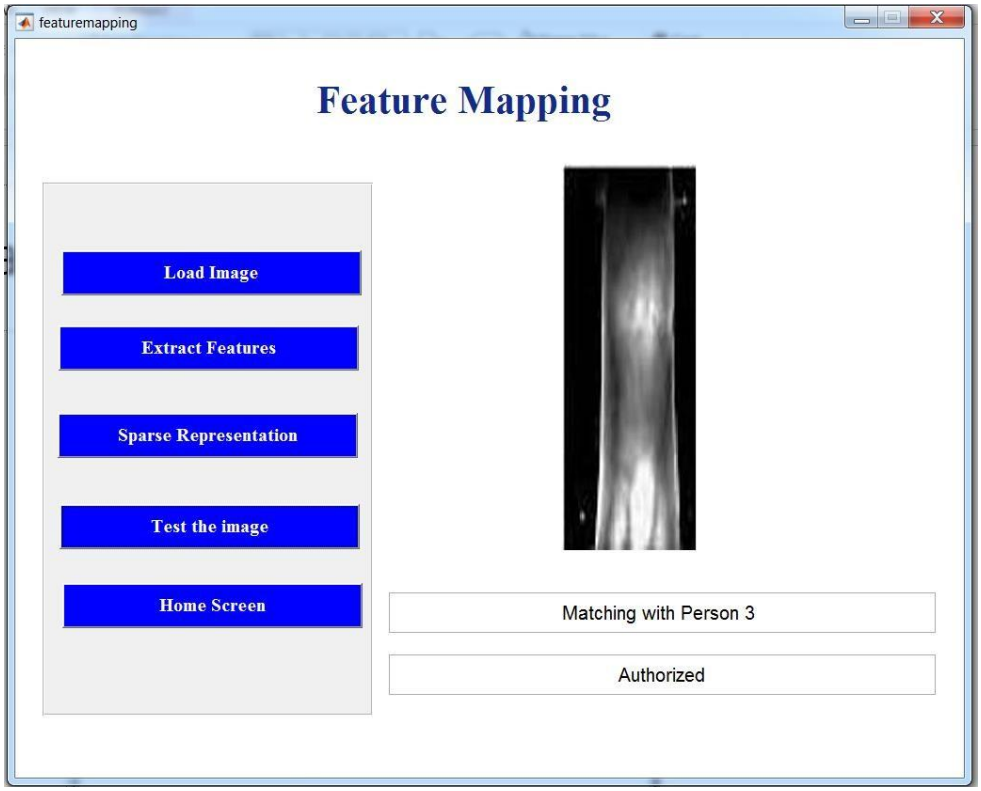

gfilterpage
Adaptive Illumination Control
Show image
Adjust illumination
Apply Gabor Filter
Home screen



E-Identification Scheme




featuremapping
Feature Mapping
Load Image
Extract Features
Sparse Representation
Test the image
Home Screen


featuremapping
Feature Mapping
Load Image
Extract Features
Sparse Representation
Test the image
Home Screen
Matching with Person 3
Authorized

CONCLUSION

This system design and implementation of real time protection and detection of vehicles with help of embedded system . By doing this project we will provides the implementationof Anti-theft detection and also provides the solution for the theft kind of activities in the vehicles . Face and Finger-vein based identification technology has high security and reliability compared to the traditional authentication mode.The project is a face & fingervein based user recognition system for biometric authentication and identification. The system provides effective and efficient features using bilateral algorithm which is been implemented on MATLAB platform. The accuracy can be further improved by considering the light exposure factor in the implemented hardware.

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