Vehicle Identification
using Fuzzy Adaline Neural Network

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ABSTRACT

Video surveillance is an important aspect in today's world, where a particular scene of area requires monitoring to avoid terrorist attacks and unauthorized entries. Vehicle recognition is an important area in object tracking and recognition. Objects may be of rigid or non-rigid in nature with varying velocity and have different features. Important features like shape, logo, color and texture are complex in nature. Hence there is a need of better algorithm for detecting and identifying the objects like car. A new method is proposed for recognizing the cars present in the video. At first the features like shape is extracted using moments, logo using the Scale Invariant Feature Transform (SIFT) and the RGB color values of the car body. Using these features the recognition is carried out to classify the type of car. Recognition of cars has range of application like, military surveillance, traffic management, autonomous navigation system, auto parking.

Keywords: SIFT, Feature Descriptors, ADALINE, Fuzzy

1. INTRODUCTION

In today's world surveillance has become an important work of interest specially, when it comes to monitoring vehicles only the manual observation of the videos are used or an automated system of number plate recognition (Zhanga and Wangb, 2012; Zhu *et al*., 2012; Parisi *et al*., 1998; Porikli and Kocak, 2006) are currently being used. What if the entire system can be automated? This gave the authors a motivation for developing a system where, when a car arrives its shape, color and make information is extracted and a description is given. The proposed approach extracts three features the shape using moments, logo using SIFT feature extraction and color using the RGB value ranges.

This study is organized as:

- Feature extraction
- Moments
- Proposed architecture
- Results

1.1. Feature Extraction

Features are the basic identity of an image; they almost describe an image uniquely. The features should carry enough information about the image and should not require any domain-specific knowledge for their extraction. They should be easy to compute in order for the approach to be feasible for a large image collection and rapid retrieval. There are various feature extraction techniques like, Scale Invariant Feature Transform (SIFT). Speeded up Robust

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Features (SURF), Harris Corner, Canny Edge Detection. The SIFT feature extraction was used for our problem. SIFT features are invariant to scale rotation and also view point variations hence even the camera angle varies by a small amount the feature extraction would be feasible and accuracy would be large.

1.2. Moments

Moments can also be used as a feature extraction technique. Moment is a certain particular weighted average of the image pixels' intensities, usually chosen to have some attractive property or interpretation. An essential issue in the field of pattern analysis is the recognition of objects and characters Regardless of their position, size and orientation. The idea of using Moments in shape recognition gained prominence when derived a set of invariants using algebraic invariants. Two-dimensional moments of a digitally sampled $M \times M$ image that has gray function $f(x, y)$, $(x, y = 0, \ldots M-1)$ is given as:

$$m_{pq} = \sum_{x=0}^{x=M-1} \sum_{y=0}^{y=M-1} (x)^p \cdot (y)^q f(x,y) \, p, q = 0, 1, 2, 3 \ldots$$

The moments $f(x, y)$ translated by an amount (a, b), are defined as:

$$\mu_{pq} = \sum_x \sum_y (x+a)^p \cdot (y+b)^q f(x,y)$$

Thus the central moments m_{pq} or μ_{pq} can be computed from the above equation on substituting $a = -x$ and $b = -y$ as:

$$\bar{x} = \frac{m_{10}}{m_{00}} \text{ and } \bar{y} = \frac{m_{01}}{m_{00}}, \mu_{pq} = \sum_x \sum_y (x - \bar{x})^p \cdot (y - \bar{y})^q f(x,y)$$

When a scaling normalization is applied the central moments change as:

$$\eta_{pq} = \mu_{pq} / \mu_{00}^{\gamma}, \ \gamma = \left[(p+q)/2\right] + 1$$

1.3. Proposed Architecture
1.3.1. Algorithm

Figure 1 Describes the architecture for the proposed system:

Step 1: Video containing cars is given as input
Step 2: The video is split into frames for further processing
Step 3: Each frame is sent for feature extraction
Step 4: Feature extraction

Feature extraction is of three stages:

Stage1: The Shape is extracted using the contour detection and the detected contour of the car is used to identify the moment value of the shape. This moment value is fed as input to the fuzzy based ADALINE neural network. **Figure 5** describes the result of shape extraction for Suzuki swift car.

Algorithm for Shape Extraction:

Step 1: Each frame is first converted to a binary image using an adaptive Thresholding where the colour image is converted into a black and white image.
Step 2: The binary image is used to identify the contour of the car using the cv Find Contour function
Step 3: The identified contour is applied Hu-moments to get the feature value **Fig. 4** describes the Hu moments values for Suzuki Swift car as input
Step 4: The error in the feature values (i.e., the amount that it does not belong to a particular shape) and the change in error is given as input to the Fuzzy Adaline neural network, based on the membership function and the error rate the neural network identifies it as to which model it belongs.
Stage 2: The Logo is extracted from the original colour frame using the SIFT feature descriptors. The descriptor's error and change in error is given as the input to the fuzzy ADALINE neural network. These descriptors gives us which make the care belongs to)

1.4. Algorithm for Logo Identification

Step 1: The extracted frame is taken as input to the SIFT feature extraction. **Figure 2** shows the feature calculation for the three brands used
Step 2: The logo area is found out by using the trained xml file.
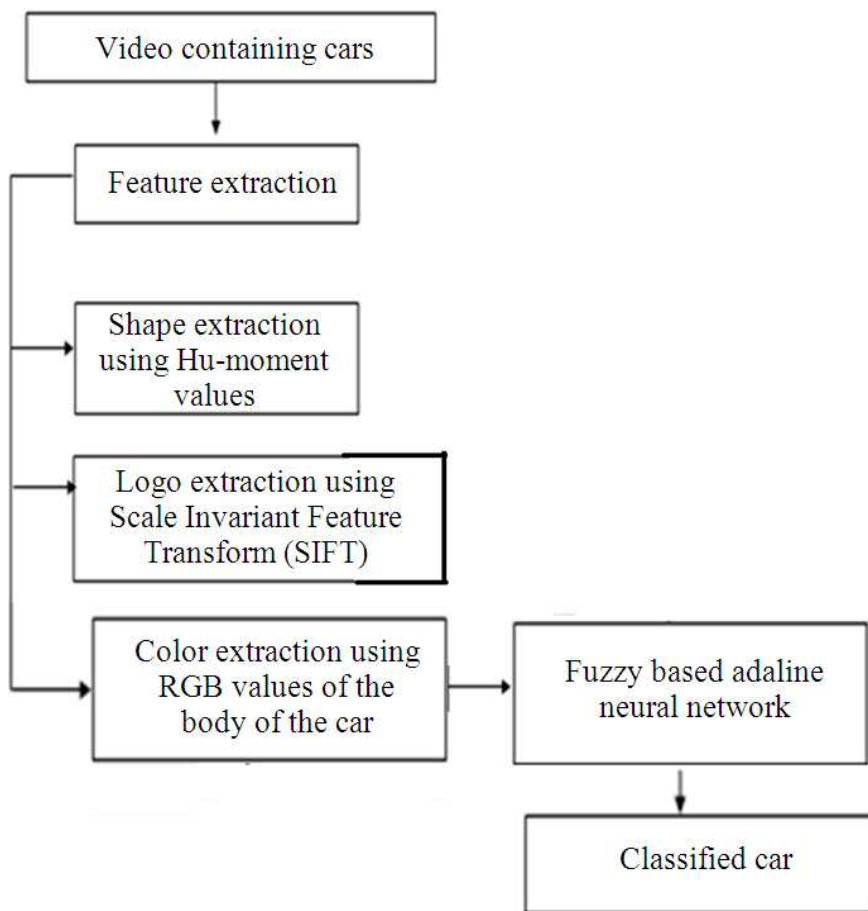Step 3: The identified logo is done a SIFT based matching with the templates found.

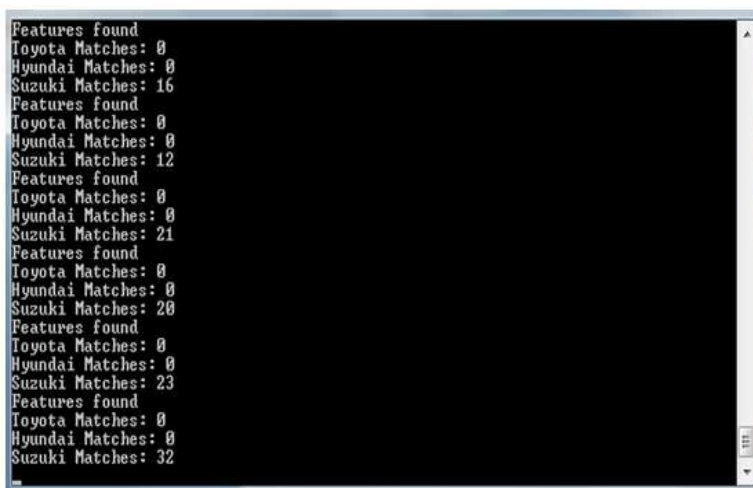**Fig. 1.** Proposed architecture flow diagram

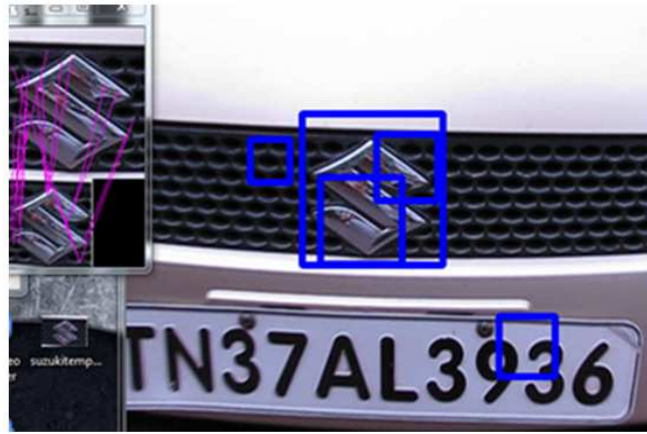**Fig. 2.** Feature calculation for the logo templates

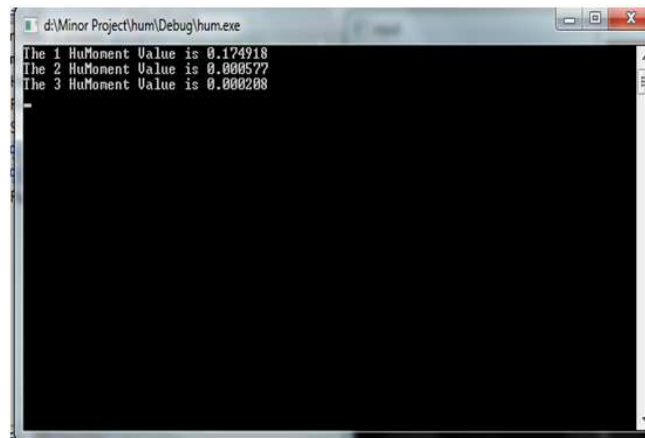**Fig. 3.** The detected feature of the Suzuki logo

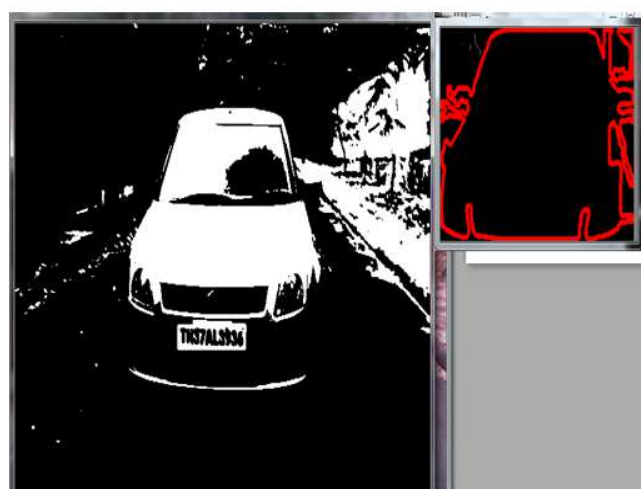**Fig. 4.** The detected Hu moments value

Fig. 5. The detected feature of the Shape for one frame

Table 1. Tabulation of results obtained

Parameter	Suzuki logo	Hyundai shape	Toyota logo	Shape	Logo	Shape
Total no of detected features	134	143	166	106	154.0	123.0
Total no of relevant features obtained	122	48	147	61	135.0	56.0
Precision	91%	33%	88%	57%	87.6%	45.5%
Recall	81%	34%	79%	48%	77.0%	33.0%

Step4: The amount of match for each make (brand) of the car is found by the SIFT matching. **Figure 3** shows the logo matching of.

Step5: The error or misclassification and the change in error of the match is taken as the input to the fuzzy ADALINE (Xindong *et al*., 2008; Psyllos *et al*., 2010; Jeatrakul and Wong, 2009) neural network.

Stage 3: The colour of the car is taken by counting the pixel values of the contour region of the car. The pixel value that has the largest count is the colour of the car.

1.5. Algorithm for Colour Feature Extraction

Step 1: The input frame and the contour frame identified in the stage 1 is given as input for colour identification.

Step 2: The area of the contour is traced in the colour frame and the pixel values are counted

Step3: The bin which has the maximum number of counts is considered as the identified colour.

Step4: The identified colour and the change in the error values as shown below is considered as the input to the ADALINE neural network. e.g., say the maximum color bin is white i.e., 255,255,255

White ratio = the amount of white pixels/the total number of pixels in contour area. Error is the other pixel values present in the area i.e., (1-white ratio). This error is considered as the input to the ADALINE neural network. The output of these stages is considered as the input to the fuzzy ADALINE neural network (Xindong *et al*., 2008; Jeatrakul and Wong, 2009; Sinthupinyo *et al*., 2009).

Step5: The feature error values are given as the input to the fuzzy based ADALINE neural network

The parameter of the neural network are as follows. Learning rule:

$$w(k+1) = 2 \times a \times e(k)p(k) \quad b(k+1) = b(k) + 2 \times a \times e(k)$$

Output:

$$y = \sum_{i=1}^{4} x(i)w(i) = x^T w$$

Error Function

$$e = r - y = r - x^T w$$

Weight function:

$$w(t+l) = w(t) + Fuzzy(e, de)$$

Where:

x(i) = Input variable
w(t) = Weight obtained at time instance t
b(t) = Weight bias value at time instance t
w(t+1) = Weight at the next time instance t+1
b(t+1) = Weight bias value at the time instance t+1
e = Error variable
de = Difference in error

Fuzzy (e,de)-fuzzy set operation between the error and the change in errory-output value.

Step 6: The output of the fuzzy ADALINE neural network (Paul *et al*., 1998) classifies the output as to which brand it belongs to the color of the car and the model of the car.

2. RESULTS

The developed system was tested with the videos obtained using a standard video camera in a controlled environment and the results are as below.

3. CONCLUSION

Car were detected and recognized based on the shape, color and logo features that are extracted from the frames

of the input video. This method can detect and recognize Hyundai i10, Suzuki Swift and Toyota Innova. The Output will be the brand, color of the car and the model of the car are detected. **Table 1** discusses about the results obtained after classification for three brand of cars. In future the scope of this work, various brands needs to be tested and speeding of the feature extraction procedure will be carried out.

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