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Cars Identification from partial images using norm angle of feature points.

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Abstract — Image processing is being widely used in various practical fields such as face recognition and medical diagnosis. Image recognition could be based on full shape or partial shape imaging depending on the area where image processing is applied. The application of interest in this paper is to use partial shape recognition to determine the brand and model of a car. Since the task of tracking partial car images is extremely important for security purposes .partial shape recognition only works on part of a car picture and uses sub matrix matching algorithms. The proposed research aims to improving on existing sub-matrix matching by norm angle calculations of features adding. We will demonstrate that the proposed new approach results in higher detection efficiency and lower error. Previous studies could do this but with the presence of at least 30% of the size of the car to give correct detection with limited efficiency. Our aim is to able to get correct detection results with minimum of 20% of car size coverage.

***Keywords*— Feature points, Object Detection and Recognition, Image Segmentation, Sobel edge detection, SURF.**

1. Introduction

As technology is developing, more classes of objects are emerging with various necessities to recognize them in computer vision. In some areas, such as face recognition, different computational models of face recognition have been developed. However, the face is comparatively rigid, and faces share fairly similar structure compared to each other. Other objects including planes, cars and automobiles are much harder to be identified by computers as there are numerous forms of each with different shapes especially when we speak "partial".

Since 1970s, object recognition on vehicle or non-vehicle has been a research interest due to its applications importance, but not so many to recognize models and manufacturers [51],[53].

Although a lot of work has been done in the past on object recognition, few among which are Farrell et al [50] and Ferencz et al [2] have addressed a more specific task of a categorized object. Farrell et al [50] suggested that the problem should be to investigate the sample using a volumetric framework in combination with an appearance model. Ferencz et al [2] considered the problem to be addressed as a visual identification and attempted to learn distinguished appearance plots.

There are numerous algorithms that have been developed in theory and techniques used to extract feature points: Harris corner detector, Scale-Invariant Feature Transform (SIFT) Matching, Edge Map, and Feature Detection and Description using (SURF). Bay et al. [22] suggested a new method for detection based on Hessian matrix [29]. This algorithm is the "speeded-up robust feature" SURF which is a combination of feature detector and descriptor. Although SIFT is highly reliable, its limitation lies in the relatively large requirements in terms of memory and extraction speed. To increase the speed of both the detection and description steps, SURF features build on the same fundamental principles as SIFT, using a certain number of approximations. Nevertheless, due to the large benefits of the performance of the detector/descriptor combination SURF has been widely used. For example Jang and Turk [14] attempted to tackle the problem of within-class car recognition by combining SURF features and bag-of-words model with structural verification techniques and validated their approach on realistic-looking toy car datasets.

After detection of feature points, comparison is required between the output and the present database to identify the car. Matching with features requires: Detection of feature points in both images and finding the corresponding pairs and using these pairs to align images.

Donoser et al. [42] explained a novel shape matching method denoted as IS-Match (Integral Shape Match). They introduced a chord angle descriptor which combined local and global information that was invariant to similarity transformations.

Petrovic et al. [62] worked on the identification of the car make and model but from frontal images only. After defining the features from pre-defined regions, they are then compared to the database cars. In previous studies, results were acceptable, but they were restricted to one technique giving less accuracy, besides they require that 30% of the size of the car is to be shown in order to make the match [9],[12],[13],[18]. In this study, the matching was made by requiring a much less percentage of the picture of the car reaching 20-25% accuracy in results.

To identify feature points in the minimum time, SURF technique was used in this paper. Then the Contour technique was used to make the match and not all the picture; this helped to reach accurate results in less points and less time, also by using this technique noise effect was minimized to a negligible rate. Then Norm angle calculation was used to give more accuracy to the recognized pattern and also helped to match two pictures with different sizes (in case zoom was used in one of the pictures).

Computational models of car recognition are interesting because they can contribute not only to theoretical knowledge, but also to practical applications. Some of these applications include investigation of car accidents, big fires, tracking partial car image for security purposes or minimizing data collection for statistics purposes, etc… This paper will set forth a model for partial shape recognition that works on part of a car picture and determines to some extent its brand and model using a sub matrix matching algorithm.

The paper is composed of different sections. The details of the major sub-algorithms will be explained throughout Sections 2-4. Section 2 explains the system layout adopted for carrying on the workas well as the concept of norm angle as shape descriptor. Section 3 provides the analysis of techniques, conclusion and areas for future study.

2. System Layout

The system is based on digital images taken for the car, that undergo, then, the preprocessing operation, segmentation, edge detection and feature points definition. The following flowchart summarizes the work done:

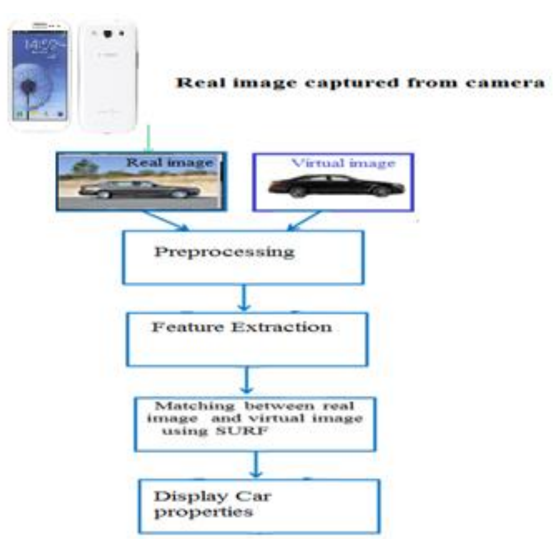


Figure 2.1: System Layout

2.1 **Image Preprocessing:**

Preprocessing consists of converting image from RGB to gray scale,and noise removal [55].

Image Segmentation:

In Segmentation, the threshold of a pixel in an image is estimated by calculating the mean of the grayscale values of its neighbor pixels, and the square variance of the grayscale values of the neighbor pixels are also calculated as an additional judge condition. First we captured the image, then we convert to Grayscale. Finally we segment the image through MATLAB.

(a) (b) (c) (d)

Figure 2.2: ((a):Real image,(b) :Gray scale image,(c): Segmented image, (d): Detected image

2.2 **Edge Detection:**

To extract edges from an image, it is essential to use an edge detector which is a high pass filter [53], [54].It significantly reduces the amount of data and filters out useless information, while preserving the important structural properties in an image [6]. In this paper, the Sobel edge detector was used. The Sobel edge detector uses two masks, one vertical and one horizontal and these are mostly 3x3 matrices [54].

Steps to find edges:

a- The first step is: Compute derivatives in x and y directions.
b- The second step is: Find gradient magnitude.
c- Third step is: Threshold the magnitude.

If we define **A** as the source image, and $\mathbf{G}_x$ and $\mathbf{G}_y$ are two images which at each point contain the horizontal and vertical derivative approximations, the computations are as follows [27]:

$$\mathbf{G_x} = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} * A \quad and \quad Gy = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * A$$

Where $*$ here denotes the 2-dimensional convolution operation

2.2.1) Example of Edge detection:

After defining the edges, I looked for contour identification. For this, only the top most (put pixels =1 for top) and bottom most car edges are considered(put bottom pixels =1). The rest of the pixels are simply filtered out and disappear from the image since these white pixels have turned into black ones.

		
Sobel edge	Top edge	bottom edge

Figure 2.3: Edge Detection Example

2. 3 **Feature Detection*:***

Feature detection is a vital factor for object recognition. Global features have the ability to generalize an entire object with a single vector. Consequently, their use in standard classification techniques is straightforward. On the other hand, the local benefit features can be calculated at multiple points in the image and thus be more powerful to an occluded and cluttered cars. However, they may require specialized classification algorithms to handle cases in which there are variable number of feature vectors per image [35].The method adopted in this paper involved matching and retrieval of distorted and occluded shapes using dynamic programming.

The algorithms and tools utilized are SURF, matching model and RANSAC. Several groups have been put into developing more efficient detector and descriptor algorithm that is called SURF. After features detection and matching the RANSAC method was used in order to eliminate outliers.

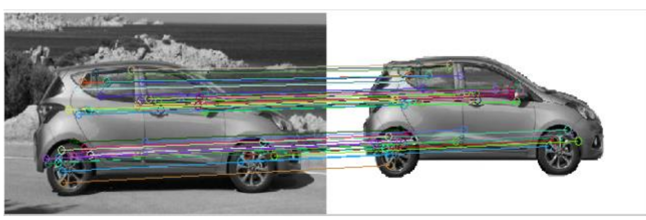


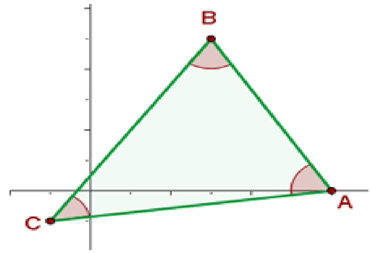
Figure 2.4: SURF matching after applying RANSAC

2.4 Calculation of Norm Angle

To calculate the angles first, we took the reference of the features point for an input image and then calculated angles between reference and the first two features then increment by one. By this step, I calculated all the angles; the same also applies for images in the database. After this, I calculated the norm angle of the difference (of input image and object template). If the norm angle is less than the threshold (5°) then good results are obtained above the threshold; else, the result failed.

Technically, I used the norm angle descriptor to get a good result for as minimum partial image occluded.

The equation of norm angle is as follows:



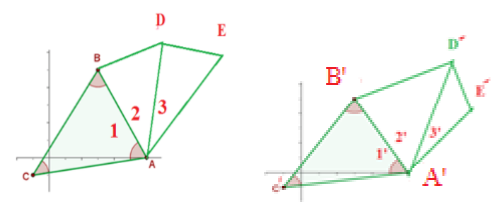
The angle between two vectors $\vec{U}$ and $\vec{v}$ is given by the formula :

$$cos\alpha = \frac{u1.v1 + u2.v2}{\sqrt{u1^2 + u2^2}.\sqrt{v1^2 + v2^2}}$$

For example: let A be the reference and B,C the feature points:

$$cosA = \frac{\overrightarrow{AB}.\overrightarrow{AC}}{|\overrightarrow{AB}|.|\overrightarrow{AC}|}$$
(3.30)

First, calculate the reference of the input image and the reference of the Template.



$$cosA1 = \frac{\overrightarrow{AB}\ \overrightarrow{AC}}{|\overrightarrow{AB}|\ |\overrightarrow{AC}|} \quad cosA'1 = \frac{\overrightarrow{AB}\ \overrightarrow{AC}}{|\overrightarrow{AB}|\ |\overrightarrow{AC}|}$$

Such that A is the reference; B,C The feature points

First, calculate the reference of the input image and the reference of the Template.

Norm Angle=√((A1'-A1)^2 +(B'2-B2)^2 +(C'3-C3)^2).

N.B: ***Threshold of norm angle=5°***

Norm angle as shape descriptor- Norm angle is calculated between features point of occluded car and database image. This special technique was selected due to the difference in shapes of samples. Size is not a matter as the identification in the database is based on this angle. So in our work, using the norm angle technique for detection of the occluded car gave the best results when the percentage of car size decreased.

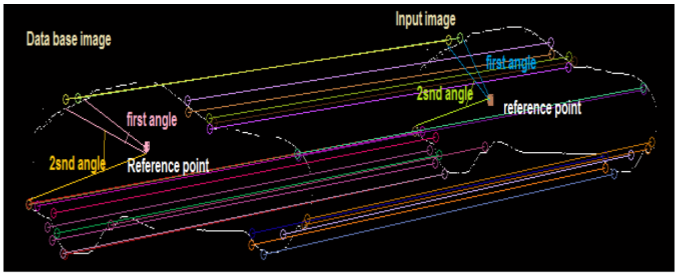


Figure 2.5: Image with Angles detection.

For this study, it is considered that if the minimum number of inliers is 6 and the norm of the angle difference is less than 5º, then the car is identical to that in the database and its model and type are identical and identified.

The system sequence could be summarized in a flowchart as follows:

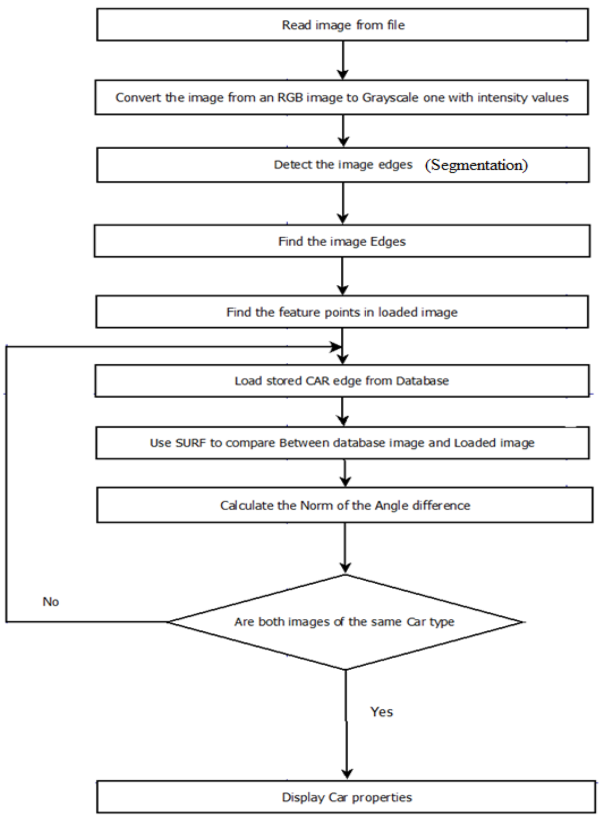


Figure 2.6: Sequence block

This part should contain sufficient detail so that all procedures can be repeated. It can be divided into subsections if several methods are described.

3. Results and Discussion

3.1 Results

Using the SURF method, evaluation was processed and the results obtained after each step is illustrated in the following figures (Figure 3.1). Using these figures, we plot as shown below the real image, the detected feature points and virtual image using the Speed-Up Robust Feature SURF. The explanation of these figures is as follows:

2D/2D feature matching using SURF methods between real and virtual image after outliers elimination (false matches) by the RANSAC algorithm. We connected the dots that match the real image to their corresponding in the virtual image

Input real image (captured from a Smartphone Samsung S3) was compared to 100 real images of cars whose data already existing in Database as could be shown in Figure 3.1.

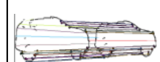
Captured image	virtual image	Gray scale image	Image segmented
			
Sobel edges	Total contour	Putative matching	Using RANSAC
			

Figure 3.1: 2D/2D test detection and matching using SURF method – Result1

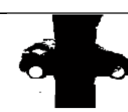
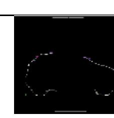
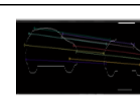
Results of an input image extracted from a S3 Samsung Galaxy smart phone camera after testing are as follows:

The given image has been correlated with:	Car Name	Car model	Car Form factor	Car Year	Norm angle	Number of inliers
	KIA	Sportage	SUV	2013	1.76253°	70

Table-1- Output result for a KIA sportage in Matlab Code.

Results of an input Car Occluded by a Tree:

The following figures explain the results of feature extraction and matching case of a car occluded by a tree

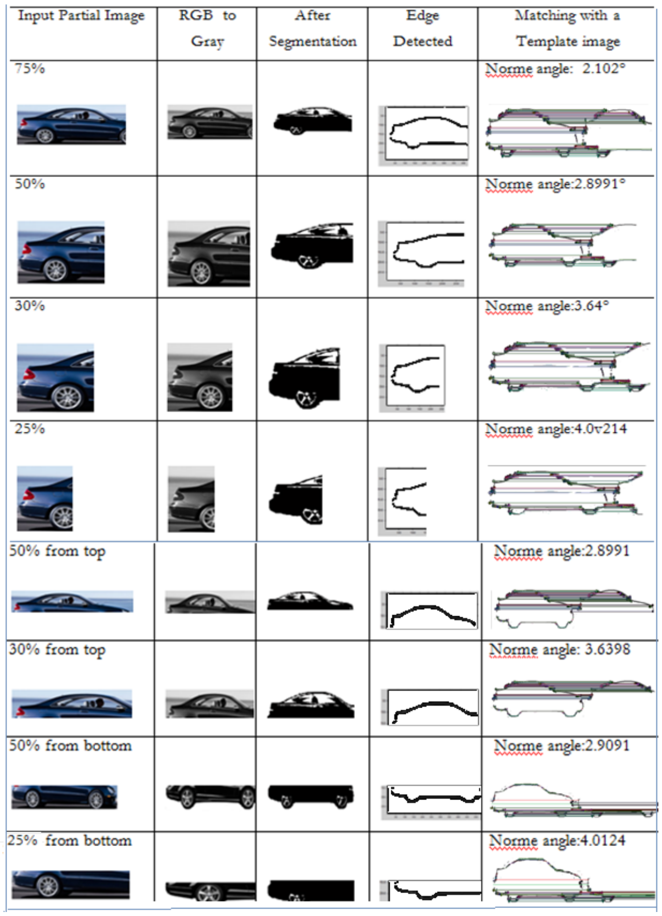
Captured image	virtual image	Gray scale image	Image segmented
			
Sobel edges	Total contour	Putative matching	Using RANSAC
			

The given image has been correlated with:	Car Name	Car model	Car Formfactor	Car Year	Norm angle	Number of inliers
	Kia	Rio	Hatchback	2013	1.7854°	9

Table-1- Output result for a KIA sportage in Matlab Code.

3.1.1)Results of Feature Extraction and Matching For Partial input Images.

The Input Partial image of the type of the car is compared to 100 different images of cars in different types, models, sizes which exists in Database:



- As mentioned earlier, the proposed research is the **use of image processing in order to determine the type of vehicles** (Toyota, Mercedes, BMW...) by analyzing a partial picture of the car.
- In my project, I did relevant tests for four different car types specifically: **Hatchback, Sport coupé, SUV, and Sedan.**

This was **based on images of real car images** captured, for a Hatchback Type for example, for four different models of cars namely: BMW, KIA, Toyota, and Mercedes
The Results are:

Car Type	Percentage of Size	100	75	50	20	<20% failed
Hatchback	Number of inliers	25	5	11	7	4
	Norm Angle	1.57°	2.094°	3.13°	3.294°	3. 5°
Sport coupé	Number of inliers	19	15	10	7	3
	Norm Angle	1.7°	2.067°	2.92°	4.139°	42.98°
SUV	Number of inliers	22	14.5°	9.25°	7	5
	Norm Angle	1.9°	1.92°	2.65°	3.853°	71.03°
Sedan	Number of inliers	12.5	10	7.5	6	4
	Norm Angle	1.1°	2.29°	3.26°	4°	37.13°

3.2 **Polynomial Charts:**

a) Relation between the Angles and Inliers for Hatchback Cars Type:

Type of an input Cars(Hatchback)			
BMW F2 (2014)	Kia RIO (2013)	Toyota corolla 40 GE (1999)	Mercedes Benz Aclass (2014)

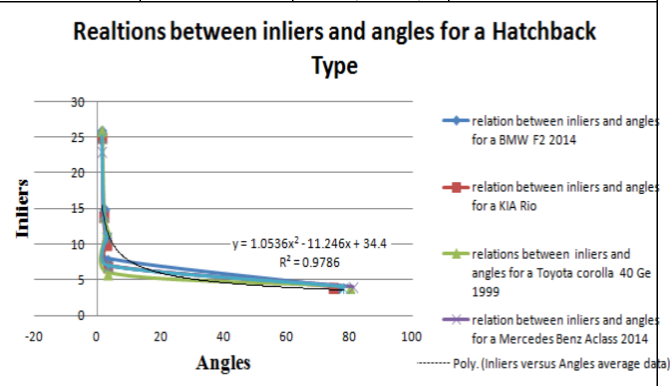


Chart 3.1: Polynomial chart of relation between inliers and angles for a Hatchback cars Type

b) Relation between the Angles and Inliers by the curve for a Cars Sport coupé Type

Type of Cars (Sport coupé)			
BMW Lead 4 Sport coupé (2014)	KIA Sport coupé (2013)	Toyota Supra Sport coupé (1999)	Mercedes benz C230 Kompressor(2002)

The following Graph provides a comparison between the Polynomial relations of an average inliers and angles for a four proposed Types for a different Cars :

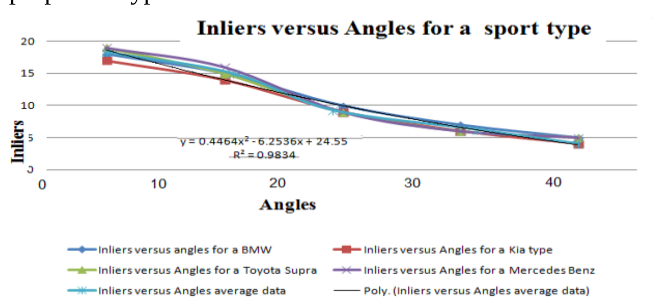


Chart 3.2: Polynomial chart of relation between inliers and angles for a Sport coupé Type.

c) Relation Between the Angles and Inliers by the curve for an SUV Cars Type:

Type of Input Cars(SUV)			
BMW X5 (2000)	Kia Sportage (2013)	Toyota 2000) Highlander(2004)	Mercedes benz ML-63-AMG (2006)

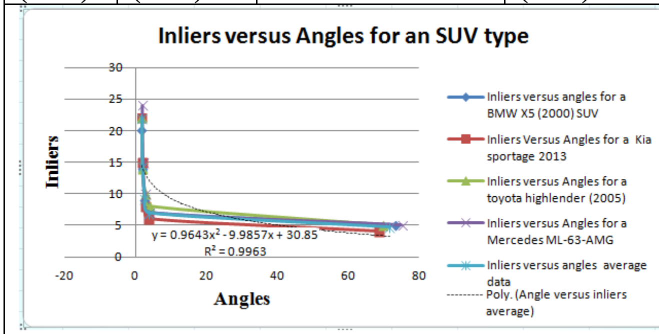


Chart 3.3: Polynomial chart of relation between inliers and angles for a Hatchback car Types

d) Relation Between the Angles and Inliers by the curve for a Sedan Cars Type:

Type of Cars (Sedan)			
BMW 7 Series LONG (2013)	Kia Sorento (2013)	Toyota Corolla (2014)	Mercedes Sedan Eclass 350(2007)

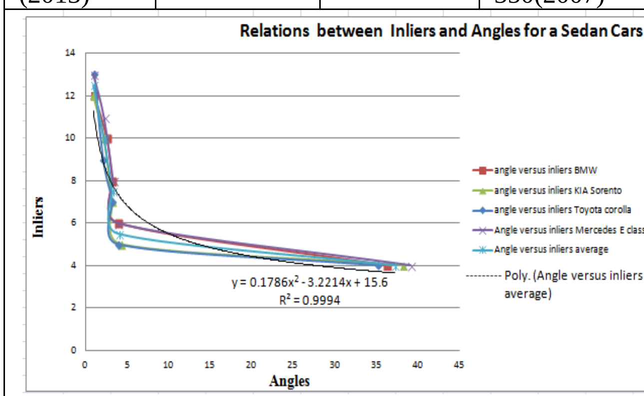


Chart 3.4: Polynomial chart of relation between inliers and angles for a Sedan cars Type

3.3 **Polynomial Equation:**

Car Types	Polynomial Equation
Hatchback Types	$y = 1.0536x^2 - 11.246x + 34.4$
Sport coupé Types	$y = 0.4464x^2 - 6.2536x + 24.55$
SUV Types	$y = 0.9643x^2 - 9.9857x +30.85$
Sedan Types	$y = 0.1786x^2 - 3.2214x +15.$

3.4 **Chart of relation between inliers and angles for all car Types :**

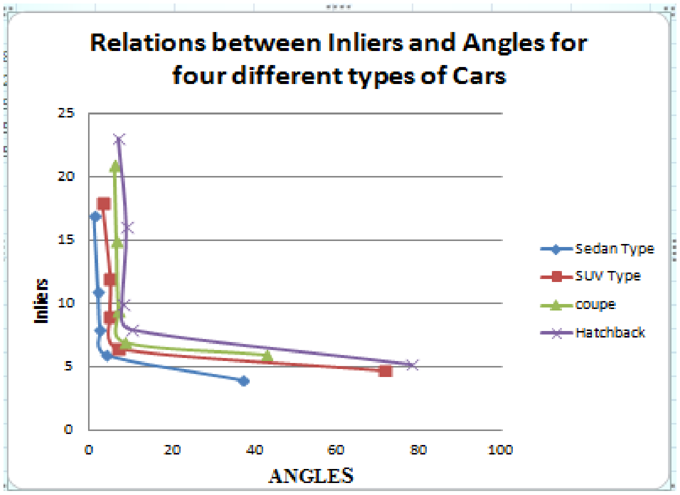


Chart 3.5: Polynomial chart of relation between inliers and angles for all car Types (sedan, SUV, Sport coupe, Hatchback)

This chart shows that there is no intersection between these line relations of each car type. This drives us to the conclusion that the classification was right in very high percentages. It is possible to know the different types of cars from the inliers and angles because each of these types has different inliers and angles as shown in Table 17, Table 18. In case of intersection between line relations of each car type before reaching 20% of car size, it will be difficult for us to verify the type of the car. But if intersection happens after 20% of car size, classification of car type will not be possible.

The blue colored line represents Sedan and it gave the best result due to its small angles measured between curves as shown in Y-axis. While taking the X-axis ,SUV gave the best result for same angles due to the presence of multiple number of feature points. Finally, we can say that Sedan gave the best result since it doesn't need multiple number of features point to be detected.

4. Conclusions

The previous studies didn't attempt to do the relations between the inliers and norm angles, these studies tackled only the matching between the features points on a local maximum curvatures [18] or pattern matching using the similarity measures [19], another studies based on calculating N angles for each sampled point of the shape [40], Turning Angle (TA) and Distance across the Shape feature (DAS) [36].

Analysis and Results: the results failed when the cars images were captured at the middle and when the image covers less than 50% of the original size of the car. It is also worth to note that through the inliers and angle I could distinguish between the different models and types of cars .This work is viable in that it does not only provide solid theory, but it also has many applications in the real world which could serve in various fields such as police security and intelligence departments. The main objective of this work revolves around the idea of exploring new applications for cameras in order to enable users to identify models of cars through partial images. This is especially important for banks, commercial companies, detectives, police, etc…. Another advantage of this is the possibility to implement it on smart phones as an application.

that helps to know all needed information about the car like manufacture place, power, type, motor speed , etc… as well the ability to detect whether cars model is being copied by another companies. Higher security on cars since it speeded up the ability to know whether the car plate of any car is stolen or not by applying the partial image processing.

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