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Automated Calculation of Distortion factor for Convex Mirror using Image Processing Technique

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Abstract: ***Rear View Convex mirror are used in vehicles to get the visibility of back sides. These mirrors are very important as they are very crucial for safety purposes. Therefore the parameters of the mirrors must be under a limit. Distortion factor is one of the parameter of rear view convex mirror. Current method for calculating Distortion factor is manual. In this paper, a novel technique for automated calculation of distortion factor is proposed using image processing techniques. Edge detection is done using particle swarm optimization and line segment is done using Progressive probabilistic Hough transform. The result obtained by proposed method is fast and accurate. Major advantage of the proposed method is that it is flexible. Various mirrors have been used to verify the proposed techniques.***

Keywords: Convex mirrors, Distortion factor, Progressive probabilistic Hough Transform, Edge detection

1. Introduction

Rear view mirrors are of two types interior as well as exterior. Interior rear view mirrors are of flat type and exterior rear view mirrors are of convex type to get a greater viewing angle. Vehicles such as cars have both interior as well as exterior mirrors whereas bikes, rickshaw, etc have only exterior mirrors. As these mirrors are used to see at the rear side they are of very importance as it avoids chances of accident. Without rear view mirrors we cannot see at the rear side and there are chances of accident while turning or while changing a lane.

So these mirrors are of utmost importance in vehicles for the purpose of safety. Various government organizations such as BIS (Bureau of Indian standards) have laid down some standards on the quality of rear view mirrors. Therefore various parameters such as radius of curvature (R.O.C.), distortion factor, reflectance, etc must be under the given specification.

All the mirror manufacturers have to pass the quality test to prove they are under specified standards. The current techniques used to calculate distortion factor has same experimental setup as the proposed method but takes the prints of the images to calculate the distortion factor manually.

Major problem in this is that there is no computerized system that exists to measure the parameters of rear view convex mirrors. As all the mirrors have to pass quality test, there is a need to develop a computerized system which can determine the parameters of rear view mirror. So in this paper, procedure to measure the distortion factor of rear view convex mirror is proposed with the help of image processing techniques. The proposed technique is verified by testing various convex mirrors. The experimental setup for measurement of Distortion factor is shown in section 3.1. The images taken from the experimental setup are used to calculate distortion factor. Various image processing techniques such as edge detection using particle swarm optimization, Progressive probabilistic Hough transform and Hough Circle detection has been used to calculate the distortion of mirror.

2. Literature Survey

Mirrors have been used in automobiles to enhance automobile driver’s ability to view his or her environment. Their size, optical properties, and placement are all regulated. Because of these regulations, and along with their importance in enhancing visibility, numerous studies evaluating the use of mirrors have been conducted. BIS have laid down some standards on the quality of rear view mirrors. BIS has created class of rear view mirror and each class specifies the dimensions and R.O.C. to be used for that particular class of rear view mirror [12]. The distortion factor of convex mirror must not be more than 5% for all class of mirrors as per AIS (Automotive Industry Standard) [13]. Rear view mirrors having specified values of parameters such as ROC, distortion factor, reflectance, etc are used in automobiles according to their use. Main focus of literature survey was to study the standard specifications for the said parameters for quality measure of rear view mirror. We need techniques to calculate the distortion that are automatic, accurate and fast.

The proposed technique uses image to calculate the Distortion factor and as shown in section 4, it all comes down to finding the exact length of the line segment for accurate determination of distortion in image. So this section also reviews the image processing techniques such as image segmentation, edge detection, Particle Swarm Optimization and Hough transform used for the proposed method as follows, Image Segmentation relates to computer vision technology. Image segmentation methods have been used to find ROI (regions of interest) in images [2]. The importance of image segmentation can be illustrated in shape detection, feature extraction, face recognition. Different algorithms have been proposed for image segmentation using thresholding, such as segmentation using histogram shape based method [2], segmentation using clustering based methods [2], entropy based segmentation [2], object attribute based method [2], etc. Basically image segmentation using thresholding refers to selecting a threshold point, at which all the pixel value below threshold is set to 0/1 and pixel value above threshold is set to 1/0.

Edges, intuitively is a set of connected pixels that lie on the boundary between two regions [1]. Edge detection is an important field in image processing. Edges characterize object boundaries and are therefore useful for segmentation, recognition, feature extraction, and identification of objects in a scene. Detection of edges refers to the method of locating discontinuities in an image. These discontinuities originate from different scene features such as discontinuities in depth, discontinuities in surface orientation, and changes in material properties and variations in scene illumination [2]. Basically, these discontinuities are nothing but sharp grey level transitions in image. Thus the basic edge detectors include the use of differential operators for edge detection. Mostly, first order and second order differentiators are used. First order derivatives are based on various approximations of 2-D gradient [1]. Various masks are used to get the first order derivative of the image such as Roberts, Sobel and Prewitt. Laplacian of an image gives a second order derivative of an image [1].

These first order and second order derivative operators give nothing but a grey level image with highlighted edges. But for most of the application we need a binary image, so that we can clearly see only the edges and nothing in the background. Also after applying the edge detection operators we need to do thresholding operation to get a binary image. This makes the process of edge detection quite manual as every image has its own different threshold point where we can extract the proper edges. In order to avoid such manual process, Particle Swarm Optimization is used for image segmentation [4]. Particle swarm Optimization is an algorithm from evolutionary computation. The purpose of using particle swarm optimization is to get an optimal solution using certain evaluation function (fitness function). Particle swarm optimization is a heuristic global optimization method put forward originally by Doctor Kennedy and Rusell Eberhart in 1995 [5]. Maximum entropy principle is used as fitness function [7]. Particle swarm optimization calculates the maximum entropy for every image automatically with its algorithm. The corresponding threshold for which we get the maximum entropy is given as optimal solution for image segmentation [7]. The edge detection algorithm using maximum entropy principle is an effective way of obtaining edges from images [6]. The proposed method applies the edge detection used in that paper with particle swarm optimization to get automated edge detection.

One of the feature extraction technique used in image analysis is Hough transform [1]. Hough transform is used to find the shape of the object by voting procedure. This voting procedure is carried out in a parameter space also called as the Hough space/accumulator space. The classical Hough transform was first developed for the detection of lines in the image, but later the Hough transform has been extended to detect positions of arbitrary shapes such as circles or ellipses. The Hough transform used today was first prposed by Richard Duda and Peter Hart in 1972, who named it as a "generalized Hough transform"[8] after the related 1962 patent of Paul Hough[9]. The proposed method uses general hough transform for circle detection by giving known range of radius to search. Progressive probabilistic Hough transform (PPHT) is used for line segment detection [10]. PPHT gives the exact length of line segment in terms of number of pixels.

3. Methodology

3.1 Experimental setup for calculating image height (h_i):

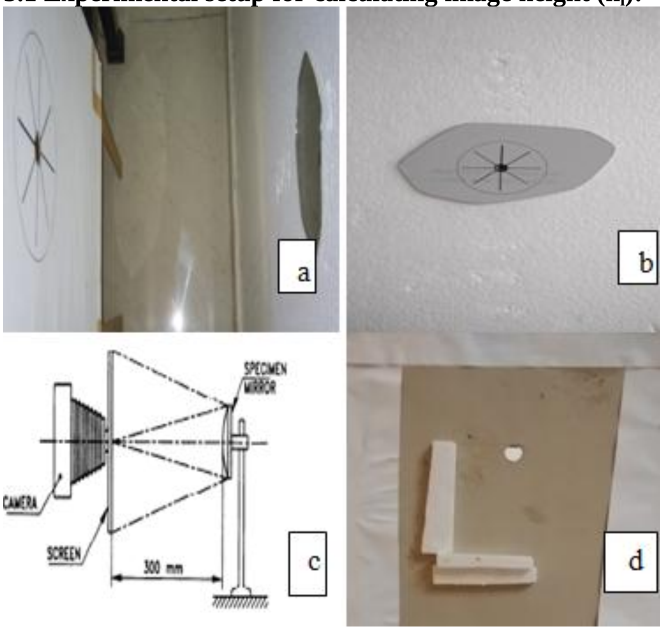

Figure 1: (a) Actual experimental setup, (b) Image obtained from camera, (c) Model experimental setup (d) Back side of screen board to place camera.

Experimental setup consists of a screen board with a circle on it. At the centre of the circle there is a hole of 10mm radius and inside the circle there are four straight lines of equal length (see fig. 1a). The screen board is properly aligned with the convex mirror in front of it, such that the image of circle in the mirror is seen though the hole (see fig. 1c). The hole is used to take the images from simple 2MP digital camera. A mirror is fixed at distance of 300mm from the screen board. The image of the board containing a circle and straight lines in it is created in the convex mirror. Digital camera placed behind the board captures the image of circle with straight lines in mirror as shown in figure 1b. The captured image is then used to calculate the distortion factor as shown in section 3.2. The straight lines are taken as an object, whose image height is to be found out.

3.2 Procedure to calculate the Distortion factor:

A distortion is a change, twist or exaggeration that makes something appear different from the way it really is. The image in convex mirror is less than the actual size of the object but that is not considered under distortion. Apart from size, if the image of an object is different in shape than it is considered as distortion. For example if circular ring is appeared as a small circular ring in a convex mirror with rest of things as same than it is not a distortion. On the other hand if a circular ring is appeared as an oval shaped ring then there is some distortion in the convex mirror. Once the image is captured we can calculate the distortion factor using the following formula,

$$\epsilon = \frac{Ro - Rn}{Rn} \times 100$$

Where, ϵ is the distortion factor in Percentage.
Rn = average length of the lines inside the circle in a reflected image which is calculated from the following formula,

$$Rn = \frac{R_1 + R_2 + R_3 + R_4}{4}$$

Where,
R_1, R_2,..= Various radial line inside the circle (as shown in figure 3.1b).
Ro = Largest or smallest radial inside the circle of reflected image.

4. Processing Methodology

In this section, image processing techniques used for calculation of distortion is explained in detail. The block diagram of processing is given in below fig.2.

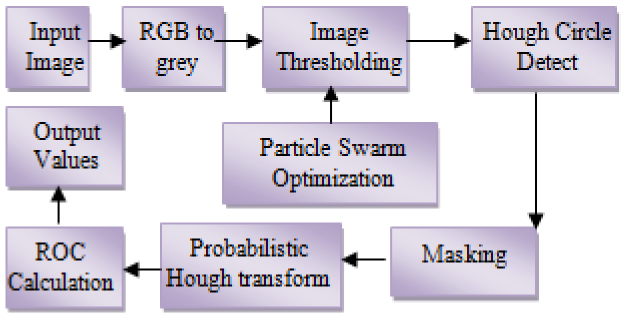

Figure 2: Block Diagram for R.O.C. Calculation

Input image is taken from the experimental setup mentioned in section 3.1. After taking the input image first operation performed on it is color image to grey conversion. The Red, Green and Blue component of the image pixel each ranging from 0-255 is summed up and divided by three to get the grey level value of the pixel. Grey level image is taken by operating every pixel of input image.

4.1 Image Thresholding

Image thresholding is a method for image segmentation. Image segmentation such as thresholding is used to find ROI (regions of interest) in images. The segmentation approach proposed in this paper is based on the concept of entropy. The concept of maximum entropy and particle swarm optimization is used for image thresholding.

In information theory, entropy gives the expected amount of information present in the symbol/message [7]. Image segmentation takes the concept of entropy in the sense of information theory (Shannon entropy), where entropy is used to quantify the minimum descriptive complexity of a random variable [7]. The entropy can provide a nice level of information to depict a given image and one can compute the entropy from the distribution of gray levels in image and obtain an appropriate partition for target image. The Particle Swarm Optimization (PSO) algorithm was originally developed in [5] as a new, simple evolutionary computational algorithm. The algorithm was developed from an inspiration given by the sharing of information between a flock of birds in process of finding food. In the artificial simulation, the behavior of each individual bird/particle is affected by either the best local or the best global individual. This makes particles constantly move to the optimal solution, and ultimately move to the global optimal solution.

In the past several years, PSO have been successfully applied in many research and application areas. Now, the PSO technique has been used to solve the problem of threshold segmentation using Maximum entropy.

4.2 Maximum Entropy Threshold Segmentation

Maximum entropy threshold segmentation arithmetic is primarily based on changes in gray-level. The entropy of an n-state system was defined by Shannon as,

$$H = \sum_i P_i \ln P_i \quad \ldots i=1,2,3\ldots.n \ (4)$$

Where pi is the probability of occurrence of the event I and $\sum pi = 1$, $0 \le pi \le 1$. The entropy of the entire image whose grey level is between 0, 1,………, $L-1$ is given as:

$$H = \sum_{i=0}^{L-1} P_i \ln P_i \ldots\ldots i=1,2,3..n \ (5)$$

Recently, two probability distributions of the image are considered: one for the object and the other for the background. Because One-dimension (1-D) entropy method doesn't take into account the spatial distribution of grey levels. Two images containing exact same histogram but with different spatial distributions, gives rise to same threshold value. The two-dimension (2-D) histogram entropies are obtained from the 2-D histogram, which is determined by using the gray level value of the pixel and the local average gray level value of the pixel. Let the average gray level for every neighborhood pixel be from *0* to *L-1*.

Let the gray level of each pixel also be in the same range. Then every pixel in original image corresponds to the pair of the pixel where one pixel has gray level same as original pixel and the second pixel has the average gray level value of the corresponding neighborhood pixel. Let $n_{i\,j}$ be the total number of pixels having grey level i of the pixel and its neighborhood grey level as j. $P_{i\,j}$ is the probability of the pair of grey level i of the pixel and its neighborhood grey level j,

$$P_{ij} = \frac{n_{ij}}{N \times N}$$

where $N \times N$ is the size of the image.

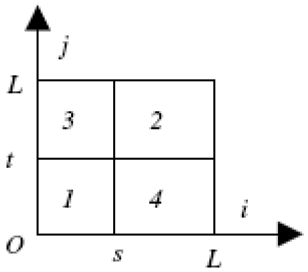

Figure 3: X-Y plane of 2D histogram [7]

Fig.3 is the X-Y plane of 2-D histogram, *1* and *2* regions along the diagonal represent the object and background. *3* and *4* regions represent the boundary and noise. Supposing *1* and *2* have different probability distribution, and thus the probability $P_{i\,j}$ is normalized by prior-probability so that the entropy of every region has additives. Let *(s, t)* be the threshold vector,

$$P_A = \sum_{i=0}^{s-1}\sum_{j=0}^{t-1} P_{ij}$$

$$P_B = \sum_{i=s}^{L-1}\sum_{j=t}^{L-1} P_{ij}$$

The 2-D entropy of *1* and *2* region is

$$H(A) = -\sum_{i=0}^{s-1}\sum_{j=0}^{t-1}\frac{P_{ij}}{P_A}\, ln\frac{P_{ij}}{P_A} = \ln(P_A) + \frac{H_A}{P_B} \quad (6)$$

Similarly

$$H(B) = \ln(P_B) + \frac{H_A}{P_A} \quad (7)$$

Where,

$$H_A = -\sum_{i=0}^{s-1}\sum_{j=0}^{t-1} P_{ij}\, ln P_{ij}$$

$$H_B = -\sum_{i=s}^{L-1}\sum_{j=t}^{L-1} P_{ij}\, ln P_{ij}$$

The probability of the information of boundary and noise contained in *3* and *4* is small, so it ignores. In the other word, the 2-D probability of *C* and *D* is *0*. The discriminant function of entropy is,

$$H(s,t) = H(A) + H(B) = \ln[P_A(1-P_A)] + \frac{H_A}{P_A} + \frac{H_L - H_A}{1-P_A} \quad (8)$$

When H(s,t) is maximized, (s, t) is the best threshold.

4.3 PSO for Image Segmentation

PSO is first initialized by a swarm of random particles. All particles search in the solution space by changing their position and velocity until the near optimal solution is found. We shall define PSO with notation and parameters required in this paper. The search space of particle in this particular application is one dimensional. The number of particles used in PSO is 5. Below mentioned flow chart in figure 4 gives the working mechanism of PSO. First of all the particles are initialized with the random threshold value. The minimum threshold value to be selected is 90 and maximum value is 140. This is because it was recorded that images from the experimental setup gives maximum value of entropy in between 80 to 150.

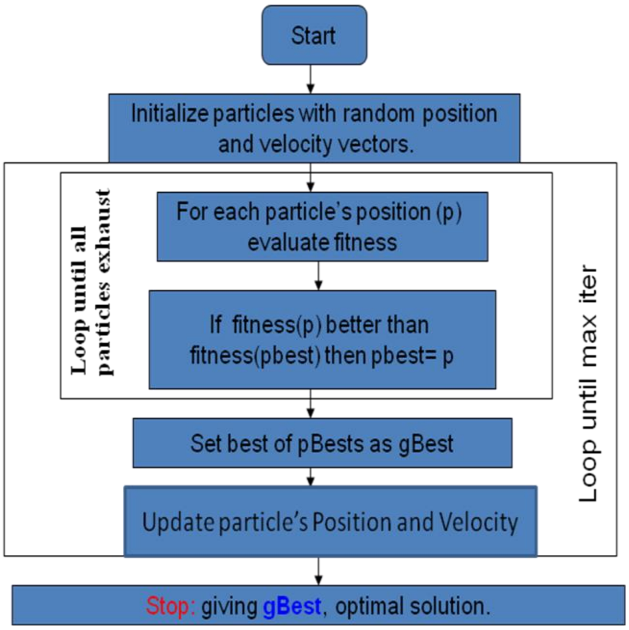

Figure 4: Flow chart of PSO [4]

After the particles are initialized, fitness function is calculated for each particle which is maximum entropy (see equation 8). If the value of fitness function is greater than previous one, then corresponding (new) threshold is set as the personal best (p_{best}). This fitness evaluation is done for all the particles. After this, the group best (G_{best}) is selected, i.e the best threshold for which we will be getting maximum entropy is selected from the group of all particles. P_{best} and G_{best} are then used to update the particle velocity and position. All particle's velocity at first has been initialized to 0. The position of the particle is nothing but the threshold which is the optimal solution. The velocity and positions are updated according to equations 9 and 10 respectively.

$$v^{k+1} = \omega \times v^k + c_1 \times (p_{best}^k - x^k) + c_2 \times (g_{best}^k - x^k) \quad (9)$$

$$x^{k+1} = x^k + v^{k+1} \quad (10)$$

Where, ω is the inertia weight, $c1$ and $c2$ are two positive constants, called the cognitive and social parameter respectively. ω is kept at 0.4 to allow to the local search more prominent than the global search. c1 and c2 are kept at 0.6 each. The first term in equation 9. v^{k+1}, is the particle's updated velocity. The second term, v^k, is the particle's current velocity. The third term, $(p_{best}^k - x^k)$, gives the difference between the particle's best previous position, and its current position. Finally, the fourth term,$(g_{best}^k - x^k)$, is the distance between the swarm's best experience, and the particle's current position. The parameters $c1$ and $c2$ provide randomness that makes the technique less predictable yet more flexible [5]. Eq. (10) provides the new position of the particle, adding its new velocity, to its current position. After the velocity and the positions are updated for all particles, the process is repeated until the termination condition is reached. The termination condition in our case is 5 iterations.

The results obtained after the segmentation is shown in figure 5b.

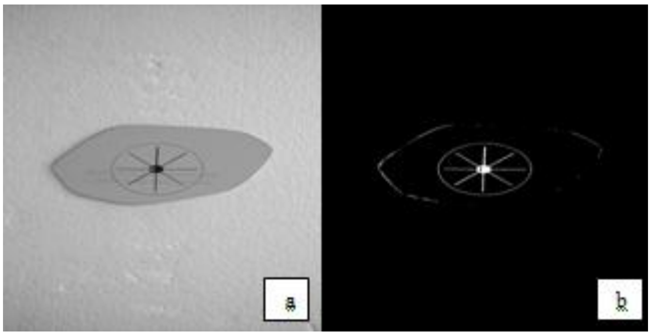

Figure 5: a: Original image, b: Thresholded image

4.4 Hough Transform for Circle Detection

Circles are a common geometric structure of interest in computer vision applications. The use of the Hough transform to locate circles will be explained in this section. This is a particular example of the use the Hough transform to search a parameter space. To determine the parameters of a circle, Hough transform can be used if a number of points that lie on the perimeter of circle are known. The parametric equations can be described for the circle with known radius R and center (a, b) as follows,

$x = a + R\cos(\theta)$
$y = b + R\sin(\theta)$

When the angle covers the full 360 degree range the points (x, y) trace the boundary of a circle. If an image has many points, some of which fall on perimeters of circles, then the work of the Hough transform is to find the parameter triplets (a,b,R) to define each circle. If the radius R is known for the circles in an image, then the search can be limited to 2D.The aim is to find the (a, b) centre location of the circle.

$x = a + R\cos(\theta)$
$y = b + R\sin(\theta)$

The locus of (a, b) points in the parameter space fall on a circle of radius R centered at (x, y). The true center point will be common to all parameter circles, and can be found with a Hough accumulation array.

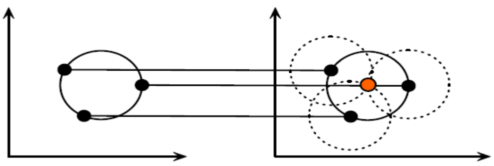

Figure 6: perimeter points of circle detecting its centre point

If the radius is not known, then the locus of points in accumulator space will fall on the surface of a cone. Each point (x, y) on the boundary of a circle will produce a cone surface in an accumulator space. The accumulation location where the largest number of cones surfaces intersect will give the triple parameter of the circle (a, b, R). The diagram below in figure 13 shows the parameter space for one (x, y) point. A circle with a different radius will be constructed at each level, r. In case of circle detection with unknown radius the range can be specified to reduce the computational time.

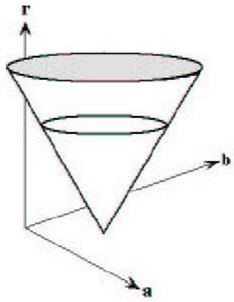

Figure 7: Hough space for circle detection with unknown radius.

In this paper, Hough circle detection is used with known range of radius. The range of radius is taken from 100 to 180 pixels. This is because the circle's radius size is not greater than 200 pixels, as the image is taken from 2 MP pixel camera and at distance of 300mm. the images of Hough circle detect is given in fig.7 below.

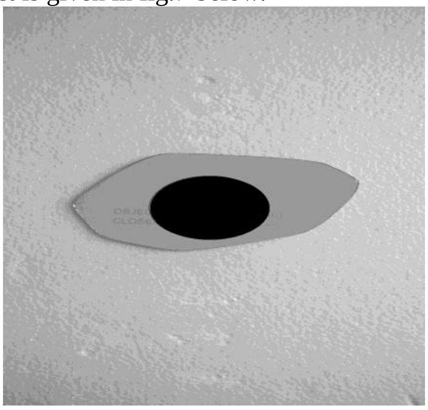

Figure 7: Detected Hough circle shown in original image

4.5 Masking

The circle is detected so as to eliminate the external edges of the mirror. The straight lines inside the circle is only required for Distortion calculation. The issue occurs after edge detection image also catches the edges of the mirrors. So to avoid these external edges of mirrors we need to detect the circle and create a mask. After the circle is detected we fill the inside of the circle with black (0 pixel value) as shown in fig.7. A mask is created of the same size of the image. It has a value of 1 at the same location where the pixel value is 0 in the image shown in fig.7. The rest of the location where the value is non zero, the mask value is made 0. This mask is then multiplied pixel by pixel with the image shown in fig.5b. The resulting image after masking is given as given in fig.8 below.

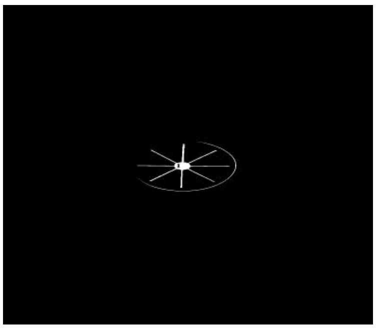

Figure 8: Masked image

4.6 Progressive Probabilistic Hough Transform

The simplest case of Hough transform is the linear transform for detecting straight lines. In the image space, the straight line can be described as $y = mx + b$ and can be graphically plotted for each pair of image points (x, y). In the Hough transform, a main idea is to consider the characteristics of the straight line not as image points $(x1, y1)$, $(x2, y2)$, etc., but instead, in terms of its parameters, i.e., the slope parameter m and the intercept parameter b. Based on that fact, the straight line $y = mx + b$ can be represented as a point (b, m) in the parameter space. However, one faces the problem that vertical lines give rise to unbounded values of the parameters m and b. For computational reasons, it is therefore better to use a different pair of parameters, denoted as ρ (rho) and θ (*theta*), for the lines in the Hough transform. These are the Polar Coordinates.

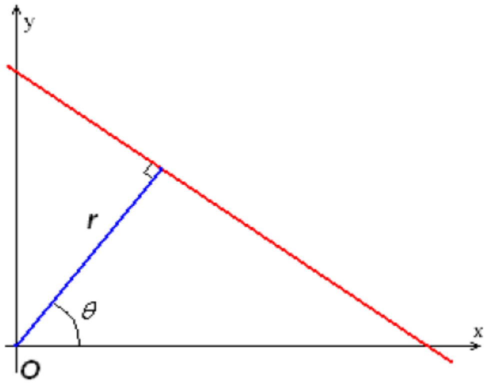

Figure 9: Polar form for line representation.

The parameter ρ (rho) represents the distance between the line and the origin, while θ (*theta*) is the angle of the vector from the origin to this closest point (see fig.9).Using this parameterization, the equation of the line can be written as,

$$\rho = x\cos(\theta) + y\sin(\theta)$$

It is possible to associate with each line of the image a pair (ρ,θ) which is unique and referred to as Hough space for the set of straight lines in two dimensions. For an arbitrary point on the image plane with coordinates, e.g., $(x0, y0)$, the lines that go through it are

$$\rho(\theta) = x.\cos\theta + y.\sin(\theta)$$

where (the distance between the line and the origin) is determined by θ. This corresponds to a sinusoidal curve in the (ρ,θ) plane, which is unique to that point. If the curves corresponding to two points are superimposed, the location (in the Hough space) where they cross corresponds to a line (in the original image space) that passes through both points. More generally, a set of points that form a straight line will produce sinusoids which cross at the parameters for that line. Thus, the problem of detecting collinear points can be converted to the problem of finding concurrent curves. But the problem with standard Hough transform is that it detects the complete line segment. The application requires that only line segment must be detected not the complete line. Therefore, in this paper progressive probabilistic Hough transform has been used [10]. The algorithm for PPHT is as follows,

Begin.

1. Check the input image, if it is empty then finish.
2. Update the accumulator with a single pixel randomly selected from the input image.
3. Remove pixel from input image.
4. Check if the highest peak in the accumulator that was modified by the new pixel is higher than threshold l. if not go to 1.
5. Look along a corridor specified by the peak in the accumulator, and find the longest segment of pixels either continuous or exhibiting a gap not exceeding a given threshold.
6. Remove the pixels in the segment from input image.
7. Unvote from the accumulator all the pixels from the line that have previously voted.
8. If the line segment is longer than the minimum length adds it into the output list.
9. Go to 1.

End

The resulting image obtained by applying PPHT is given in figure 10 below.

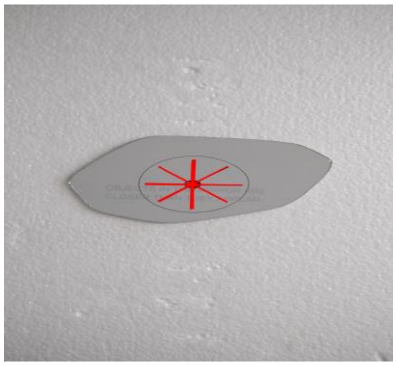

Figure 10: Line segment detected image.

The line segment detected by PPHT gives the length of line in terms of pixels. The length of line required for the application is in units of mm (mille meters). The conversion of pixel length into mm is done by multiplying the number of pixel with a scalar mm/pixel. The scalar is calculated by first taking an image of line, whose length is known. The camera used is same and the angle for taking the image is also same as for the experimental setup. The line length is then calculated in terms of pixels and as the actual length of line is known in terms mm, we can calculate the scalar in mm/pixel. This scalar is then multiplied with the pixel length of lines shown in fig.10 to get the length of lines in mm.

5. Results

Four mirrors have been taken to verify the proposed method used for calculating Distortion factor. The output of proposed method is compared with the values of previous method. In case of previous method, the experimental setup was same but the image taken by camera was printed and distortion was calculated manually. Below table 3 describes the performance of the proposed method by percentage accuracy obtained when compared with the standard manufacturer values.

$$\text{percentage accuracy}\,(\%) = \frac{\text{proposed method value}}{\text{standard value}} \times 100$$

If the accuracy obtained by above formula is 100, then subtract it by 200 to get normal % accuracy. The results for Distortion test is given in table 1 below. The scalar factor is 0.197mm/pixel.

Table 1: Results for Distortion test

Mirror	*Manufacturer value(mm)*	*Previous manual method*	*Proposed method*	
		(Value) %	*(Value) %*	*% Accuracy*
Truck	<4%	0.74	0.73	98.64
Car	<4%	0.51	0.51	100
Bike	<4%	0.92	0.91	98.91
Non gear	<4%	0.54	0.54	100

6. Conclusion

Input image is taken from experimental setup and the proposed methodology is applied over it to get the respective results. The accuracy obtained for distortion factor test is over 98%. The proposed system takes approximately 10 seconds to give results of Distortion test which is quite less as compared to previous manual method. Proposed system is very time efficient and free from human error.

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