International Journal of Computer Science, Communication & Information Technology (CSCIT)
Vol.8 pp. 12-16

Measurement Of Tyre Cord Density By Eliminating Hot Spots : A Computer Vision Based Method

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Abstract— **This paper presents a simple and a novel approach to measure cord density of tyres . Our algorithm first finds the region of interest using Hough transform to find a line, on which the fabrics or wires of the cord are aligned in collinearity, to eliminate noise and irrelevant components on the cord images after image processing and component labelling. The algorithm determines range of the amount of area that a cord component must have in terms of pixel count. The nearest shared neighbours of each components having suitable area are marked according to the distance threshold. This threshold is determined as a function of mean component area and mean distance of the components in the region of interest is also used as a clustering rule and specifies minimum distance allowed between two valid component so that any set of valid distinct components can not form a cluster. After counting all the valid components taking into account shared neighbours, to investigate if there is an uncounted labelled valid component, our algorithm expands the region of interest using the last valid component counted under assumption that y coordinates of centroids of all the valid components must be nearly collinear. Experimental results show that accuracy of the measurement method for counting wire components in tyre cord is %97,6.**

***Keywords*— Visual Inspection, Clustering, Pattern Recognition, Object Counting, Tyre Cord Density**

I. Introduction

Counting textile or steel tyre cords is an essential process for quality control in tyre industry. However cord counting is tedious, time consuming, labour intensive, error-prone since cords are thins and there may exist hundreds of tyre samples, and the counting process is usually manually performed by trained technicians. Given area of a piece of tyre, cord density is calculated easily.

Numerous studies have been conducted on the process of counting the numbers of objects. For example proposed method in [3] combines support vector machine with radial basis function as the classifier to recognize bacterial colony counting. In [4] Monlica Wattana et.al proposed a method for counting soybean seeds by separation of soybeans using the distance transform and the region growing method. In [5], a die segmentation region detection algorithm based on vertically and horizontally cumulative histograms and die detection algorithm based on YCbBr color space. In [8], a labelling algorithm to count the objects of interest which are overlapped.

One of the most important aspects for detection object is suitable illumination. Reflection angle of the light from the surface of the object and amplitude of illumination intensity effects efficiency of computer vision and image processing algorithms. In [6] and [7] numerous lighting techniques are illustrated. Despite partial bright field or directional lighting is the most commonly used vision lighting technique, it is much less effective when used with specular surfaces, generating hotspot reflection. Diffuse on-axis lighting ensures that no hotspots are reflected at the camera where the surface is more or less flat. However where the specular surface is undulating or uneven, such as a cut rubber combined with steel or textile cords, more expensive illumination solutions should be used.

In this study, we present an automatic counting method under fluorescent light illumination for aligned steel or textile cords focusing only image processing and computer vision algorithms without taking into account specific illumination requirements.

The rest of the paper is organized as follows. Section II describe our method and approaches to the region of interest and shared neighbourhood of steel cord and textile cord. Section III illustrates two experimental results. First one is counting the steel cord components in a rubber based compound, and the other one is counting textile cord components in a rubber based compound. Section IV describes conclusions and required works in the future.

II. Proposed Method

The proposed method has starting steps as capturing the cord image, image processing, connected component labelling , determining region of interest using Hough transform to find the components aligned in a line, using the components intersected by the line determine a second line that centers a set of labelled components, calculating average width (W) of the components intersected by the second line, defining the limits of the region of interest in pixel numbers as

ISSN 1737-930X

$$ROI_{+x,-x} = mean(centroids_x) \pm \frac{W}{a} \quad (1)$$

$$ROI_{+y,-y} = \pm image \quad (2)$$

where $centroids_x$, a, $ROI_{+x,-x}$, $ROI_{+y,-y}$ are mean value of sum of value of x coordinates of labelled components intersected by the second line, scaling factor of ROI, limits of the region of interest on x direction, limits of the region of interest on y direction, respectively. The figure 1 shows summarized flow diagram of proposed methodology.

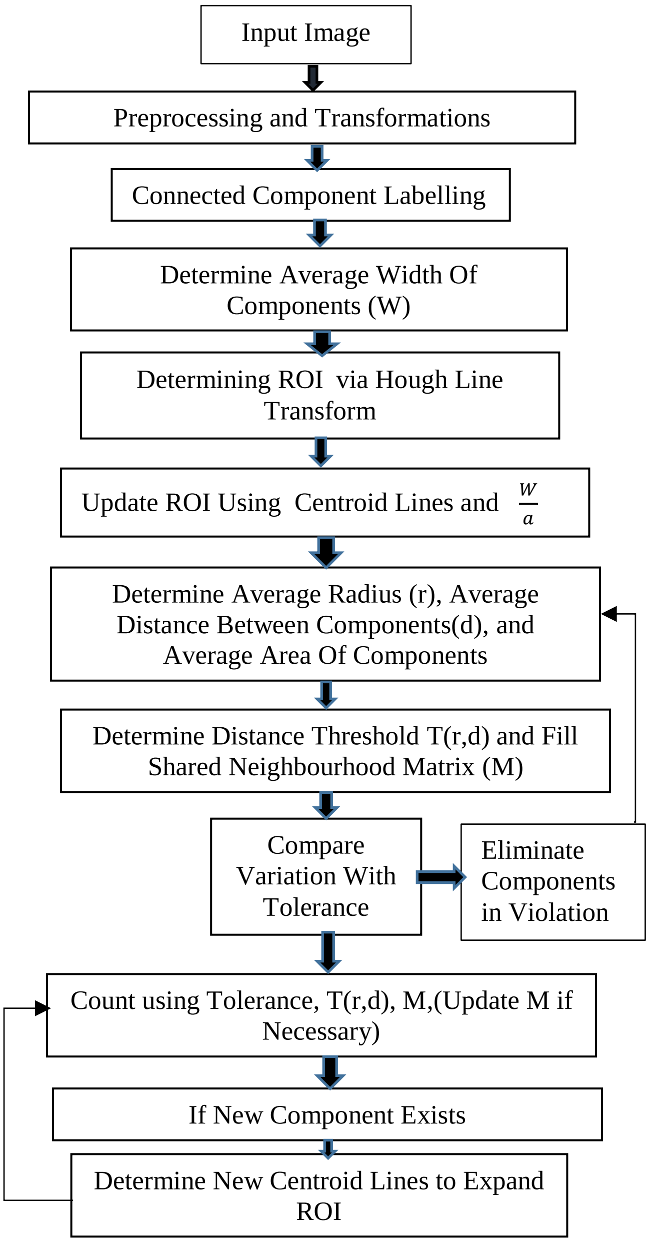


Fig. 1 Flow Chart Of Methodology

Preprocessing stage of the input image involves filtering. The lines with cord components are illustrated on the preprocessed cord image in figure 3. The line with slope is found with Hough transform. The leftmost perpendicular line is calculated via the centroid components and the rightmost perpendicular line is calculated via the centroid selected by intermediate counting process. Distance threshold for testing shared neighbourhood is defined as:

$$T(r,d) = \begin{cases} r & if \ \frac{d}{2} \geq r, \\ \frac{d}{2} & if \ r > \frac{d}{2}, \end{cases} \quad (3)$$

where r, d are mean radius of intersected components by the first line and mean distance between each labelled and intersected component, respectively.

$T(r,d)$ is also used as a clustering rule and specifies minimum distance allowed between two valid component so that any set of valid components can not form a cluster. After finding $T(r,d)$ nearest shared neighbourhood matrix M is filled with the following rule as in [2]

$$if \ there \ is \ a \ component \ j \ having \ a \ neighbour \ k \ which \ has \ a \ neighbour \ i \ such \ that$$

$$D(j,k) \leq T(r,d) \ and \ D(i,k) \leq T(r,d) \quad (4)$$
$$M(i,j) = 1$$

where $D(.)$ *is* distance between two component. Other algorithm steps are constructed as follows.

Calculating minimum and maximum allowed component area value is determined like as in [1] with a difference, which is to take into account the ROI as follows

Calculate Mean Area:

$$Avg = \frac{1}{N} \sum_{i=startindex}^{k=endindex} Area_i$$
$$for \ MinCriteria \leq Area_i \leq MaxCriteria \quad (5)$$
$$initially, \quad MinCriteria = 0,$$
$$MaxCriteria = image \ size$$

Fig. 2 Example Input Image of The Piece With Steel Cord

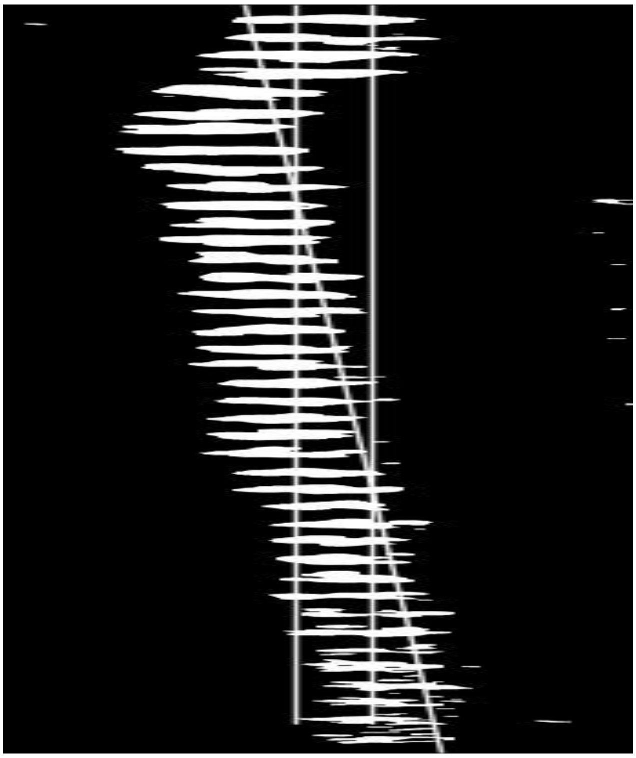


Fig. 3 Preprocessed Image With The Lines

where,
$startindex, endindex, Area_i, MinCriteria, MaxCriteria, N$ are index of the first component which has area within the area criterias in the ROI, last index of the last component which has area within the area criterias in the ROI, area value of component i in terms of pixel count, minimum area value allowed for a valid component, maximum area value allowed for a valid component, number of the components which have area size within the area criterias in the ROI, respectively.

Calculate Standard Deviation:

$$StdDeviation = \sqrt{\frac{1}{N}\sum_{i=startindex}^{k=endindex}(Area_i - Avg)^{\,2}} \qquad (6)$$

Calculate Variation:

$$Variation = \frac{MaxArea - MinArea}{Avg} \times 100 \qquad (7)$$

where $MaxArea, MinArea$ are components having maximum and minimum area within limits in the ROI. Decision of which component should be eliminated is done using aforementioned components by averaging them:

$$Avg_{ext} = \frac{MaxArea + MinArea}{2} \qquad (8)$$

After this stage $MinCriteria$ and $MaxCriteria$ are updated to obtain a tight band.

Update The Limits Until Variation Ends Changing:

$if(Avg_{ext} > Avg)$
$\{MaxArea = Avg + Std\text{Deviation};$
$MinCriteria = MinArea;\}$
$else$
$\{MaxArea = Avg - Std\text{Deviation};$
$MaxCriteria = MaxArea;\}$

To obtain optimal limits we iterate aforementioned steps until $Variation$ converges to $Variation_{th}$ which gives most accurate results. To determine lower and upper bounds for selecting the component to count, we use following formula

$$LowerBound = \left(1 - \frac{Variation_{th}}{200}\right) \times Avg$$

$$UpperBound = \left(1 + \frac{Variation_{th}}{200}\right) \times Avg$$

In the first step $LowerBound$ and $UpperBound$ are used to count the components. To investigate if there is a uncounted labelled valid component, our algorithm expands the region of interest using the last valid component counted under assumption that y coordinates of centroids of all the valid components must be nearly collinear. To expand the region, a new line that passes across the centroid of the last valid element counted is created. This last element has the maximum index number among the valid components in ROIs. The final count is calculated taking into account $T(r,d)$ and neighbourhood tests. If expansion of the ROI results in infinite loop then expansion is canceled and found counted value is specified as valid value.

III. Experimental Results

Proposed approach is tested on both steel and textile cord samples. Steel cord sample is illustrated in figure 2, textile cord sample and their processed digital images are depicted in figure 5-a and figure 5-b, respectively. The implementation of the counting algorithm has been done in C++ using openCV 4.0 library and tested on Intel Core i7 2.7 GHz Processor running Windows 10 operating system.

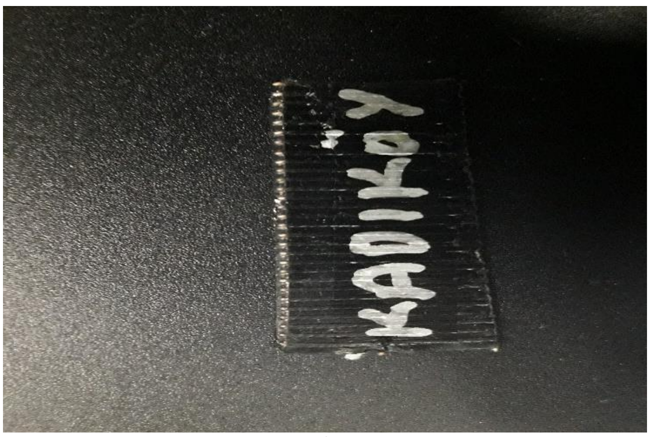
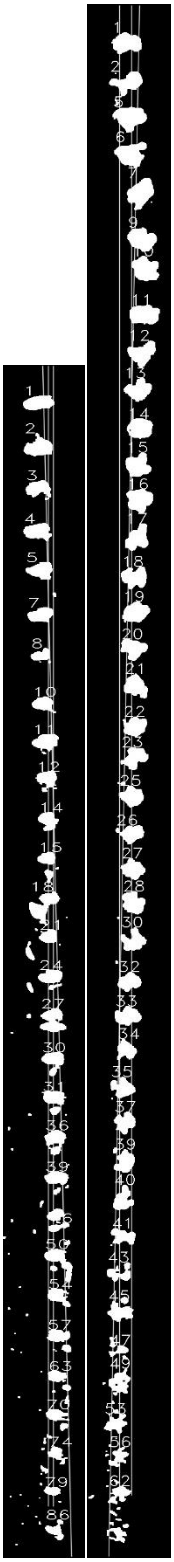


Fig. 4 Example Input Image Of Sample Piece With Textile Cord

Experimentation has been performed with a camera having 13 MB pixel resolution on a near black coloured background. In figure 4 hotspots and noise components are clearly visible, determining the ROI automatically these components are eliminated during counting process.

ISSN 1737-930X



a) b)

Fig. 5 a) Result Image Of The Sample Piece With Textile Cord(a=∞), b) Result Image Of The Sample Piece With Steel Cord((a=4),)

TABLE I

	SAMPLE CORD TYPE			
	STEEL	TEXTILE	STEEL	TEXTILE
SET TOLERANCE	170	150	170	150
a	W/4	0	W/4	W/4
ROI EXP. ON Y	YES	YES	NO	YES
ACTUAL #	41	29	41	29
RESULT #	40	29	39	X

Numbered components are the counted objects. Each number is a label of corresponding component.

Experimentations showed us three parameters; tolerance, a and occurrence of expansion of ROI. Table I illustrates effects of these three parameters on algorithm performance. One can see that ROI expansion on X axis causes infinite loop and counting process fails in case of textile cord. On the other hand ROI expansion on Y axis increases performance of the counting algorithm in case of steel cord.

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In the second stage of the experiments, we tried to investigate effect of exposure time and lighting angle on the image .

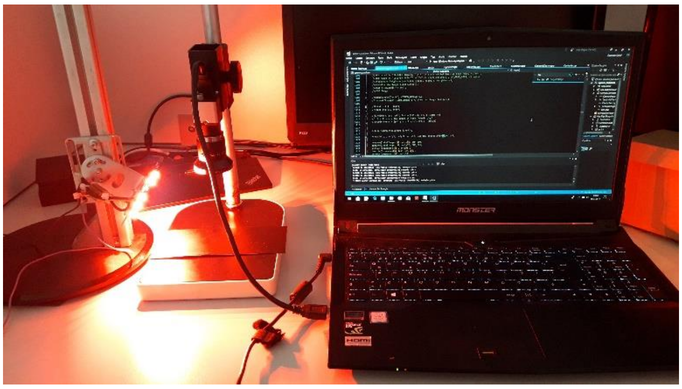

Fig. 6 Investigation of Effect of Exposure Time and Light Angle On Image Quality

ISSN 1737-930X

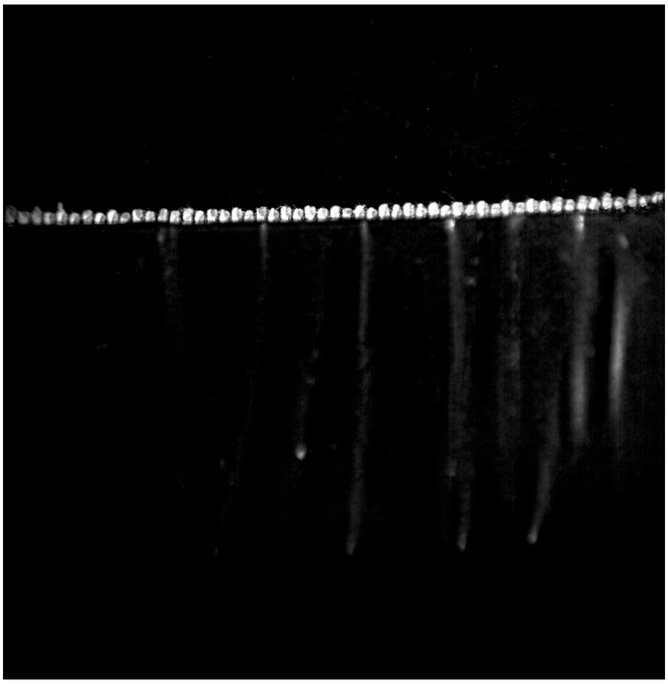

Fig. 7 Image Of Cords: Light Angle is Near $+90^0$

Using red led lights, it is observed that increasing light angle increases hot spot numbers in the image. Also making closer the distance of the light source makes same effect as increasing the light angle. Other side effect is reflections from lens of camera itself. These reflections are eliminated by decreasing distance of the light source to the cords or decreasing exposure time or doing both

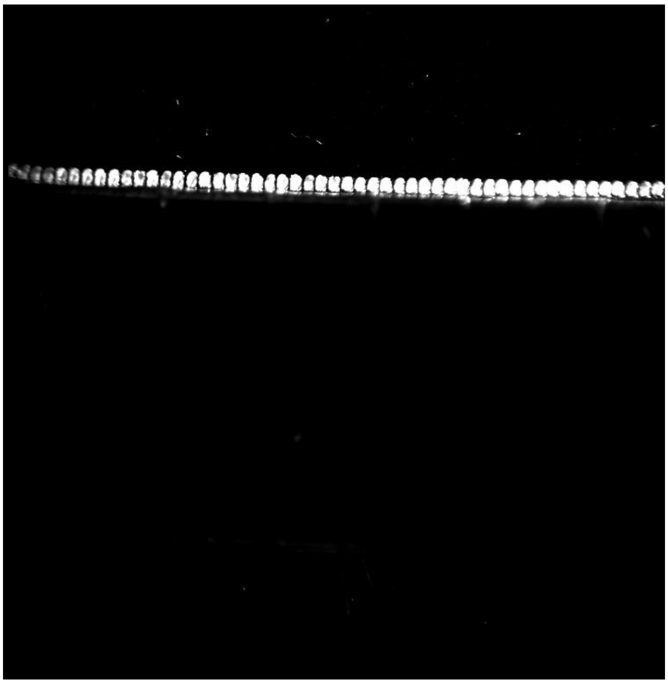

Fig. 7 Image Of Cords: Light Angle is Near $+90^0$, Exposure Time Decreased

IV. Conclusions

Counting number of cords in tyre compound is a tedious and error-prone task during inspection process. Automating this task using machine vision reduces the load on humans and also provide near accurate results with minimal work. Efficiency of the proposed method are supported with experimental results. To improve performance of the algorithm a tolerance value depending on variation of distances between components can be taken into account. Note that experimentation was performed under low quality illumination and the camera lenses were not dedicated to machine vision applications. In the second stage of experiments we used IDS 2048x2048 industrial camera by which we could adjust exposure time to eliminate hot spots on images. Adding red led light to create appropriate illumination and changing the angle of the light source, we obtained better quality images on which our algorithm can work more effectively.

Acknowledgment

This research was supported by Pirelli Automobile Tyres Incorporated Company under ongoing projects in the company.

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ISSN 1737-930X