Visual tyre defects detection Mechanism Curvelet feature

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Abstract

Automatic defect detection is an important and challenging problem in industrial quality inspection for various industries. After the manufacturing of tires, we approach the analysis in tire by curvelet transform to detect defects in tire surface.In this model, deep image features can be learned and subsequently used for detection, classification and retrieval tasks by using larger coefficients in sub-highest frequency band is represented by the feature of curvelet. We probe into deep learning based image classification problems with application to real-world industrial tasks. The experimental results show that the proposed method can accurately locate and segment defects in tire images.

Keywords:, Tyre defects, Threshold, Curvelet Transform, Local edge estimation.

Introduction

Automatic defects detection mechanism is the most significant technology, thereby reducing the vague defects impacted in the tyre while manufacturing . In India, the average life of tyre is around 6 years, which may run upto 50,000 kms on indian roads, although to increase the life of tyre by using the proposed mechanism will get over it. The proposed detection method can greatly improve the accuracy of the tyre and intact with the better quality. The quality tire production depends in the tyre builders who are trained and supervised , never the less tyre builders are often put on the assembly line for long shift where they are pressured deeply to deliver a number of tyre every shift to meet their requirements.

More work has been done on automatic tyre defect detection and has been applied in curvelet transformation.In this paper we focus on detecting broken or missing wires in the tread region, by an automatic mechanism

Figure 1: Due to improper detection mechanism

using curvelet transformation by local edge estimation. It can consist of edge magnitude computation, Guassian filtering, co-efficient selection, locating edges, threshold calculation and visual inspection.

.According to the Jobst Brandt, the rolling ressistance of tubular tyres , which is caused by flexing, judging from some tires found on the market and the growing graph is

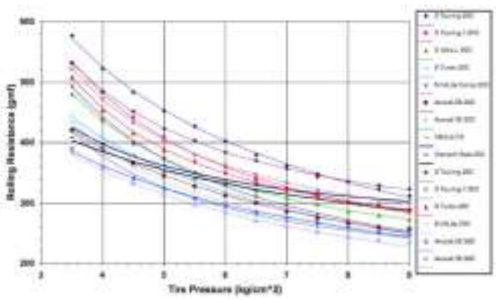

Figure 2: The Rolling resistance of tires

mentioned below. The results were plotted on graph that showing the differences that shows the consistency of the measurements and tire response.

I. Literature Survey

a) Curvelet Transformation

The Curvelet transform is a higher dimensional generalization of the Wavelet transform designed to represent images at different scales and different angles.. Curvelets remain coherent waveforms under the action of the wave equation in a smooth medium.

In this detection mechanism, the curvelets are very mandatory to overcome the defects and emphasis the defects very clearly. And curvelets are an appropriate basis for representing images which are smooth apart from singularities along smooth curves, where the curves have bounded curvature, i.e. where objects in the image have a minimum length scale.

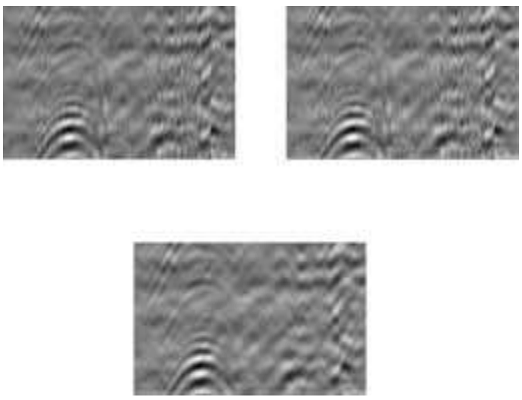

Figure 3: Image Retrieved from Curvelet Transformation .

b) Open CV

OpenCV supports some models from deep learning framework like Pytorch, Tensorflow, Torch and so more. In this detection mechanism ,we are going to use Pytorch for developing and training neural network based deep learning models.

Simply , Open CV is the library used for the image processing for various purpose.It works like to analyse the data from the camera of an Embedded system or your computer or anything that captures. The image processing is done here with help of Open cv and packages . These parameter are the mandatory things to get over the defects of the tyre .

c) Pytorch

Pytorch is the one of the most used library for deep learning models.The neural networks like Recurrent Neural Network(RNN), Convolutional Neural Network(CNN), Normal Neural Network can do with this library. A classical CNN consists of convolutional layers, pooled layers, and fully connected layers. CNN apply multiple filters to the raw pixel data of an image to extract the valuable details. In this defect detection mechanism, the pytorch module is most significant parameter to converts the images into required format that the curvelet transformation can process the images or data.

PyTorch is an open-source deep learning framework which is used for implementing network architectures like RNN, CNN, LSTM, etc and other high-level algorithms. It is used by researchers, business, communities of ML & AI. PyTorch is an open-source machine learning library for Python, based on Torch, used for applications such as natural language processing.The Most significant feature of the pytorch is Native support, east to use API, Dynamic computation graphs, too fast and it supports CUDA. These several features are the amiable to our defect detection mechanism. And it allows to process faster than other several libraries .

d) Torch Vision

The torchvision package consists of popular datasets, model architectures, and common image transformations for computer vision. These package consists of many models namely Resnet models , Alexnet models, Densenet models, VGG models .

In this mechanism, we are going access the Resnet models, which is suitable for online training data. There are variations in Resnet models like Resnet 18, Resnet 34, Resnet 50, Resnet 101, Resnet 152.In our proposed mechanism, Resnet 50 is the suitable one to do our image processing of tyre.. It provides a flexible N-dimensional array or Tensor, which supports basic routines for indexing, slicing, transposing, type-casting, resizing, sharing storage and cloning. This object is used by most other packages and thus forms the core object of the library.

II. *Proposed Work*

a) Purpose of the work

This paper intends to detect the minor defects like side wall damage, tread separation,segmentation of manufactured tyres.This is done through a Web application by collecting the real-time data as images and check with our trained data sets in our cloud.. The data is then extracted from the cloud and analysed by open CV, Pytorch , that is used for it. The analysed data is passed through the checker engine where the data set is checked by already trained dataset. Depending upon the data feed from the engine, the defects implicated in tyre are classified as per types and damage percentage.

b) Data Set

Data collection is the initial and main step in our project life cycle. In our project, experimental dataset consists of 586 tyre images of the defective tyres and 335 tyre images of good condition tyres. The defective tyres images including Tread wear indicator(TWI),scorching defects, sidewall, wobbling of tyres and tread seperation images. The real-time data is collected from the Quality manager with their helping teams under the quality unit. .All types of defects are treated as detection targets, so our target is going accomplished because of our quality members. The Quality managers are people who works under the administration, thereby the tyres images are captured and put all the captured images in the container. The captured images having unique ID , that helps finding the defective tyre, after completion of the test. The Quality managers from the sectors play a vital role in collecting and updating the data. As we are getting real time data from the quality unit, we can easily import the data container and give the output related to the each and every tyres. .The overall architecture of our approach is illustrated below.

After importing of data, our system is ready for processing. The image is preprocessed and lead into the separate module consist of curvelet transform, co-efficient selection and inverse transform . After completion of that module, the processed images is led to another massive module consist of Guassian filtering, local edge estimation, Edge magnitude computation, locating with Non Maximum Supression(NMS) and Threshold Calucaltion. After completion of this module , the output edge image is generated.

c) Data Analysis

The large set of data entered by the Quality manager is processed in the first

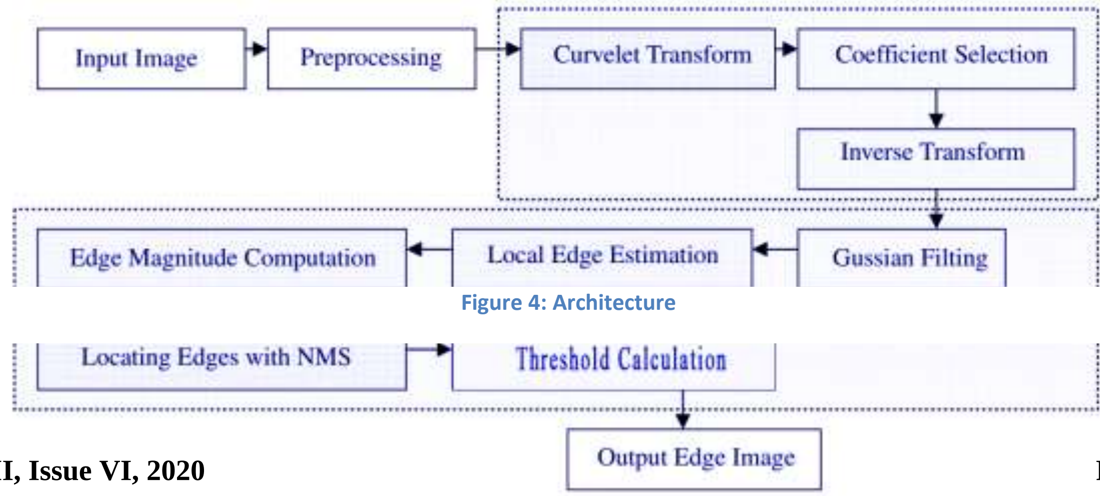

Figure 4: Architecture

module, where the curvelet transform helps the image converted into required format for processing the edges.

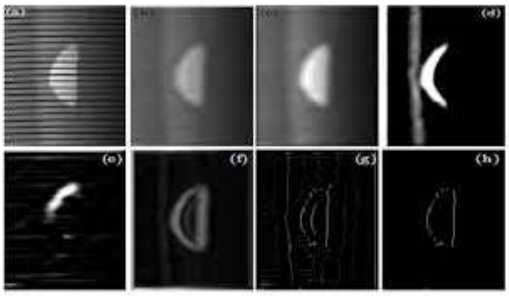

Figure 5 Coefficient selection of preprocessed image

vAfter this stage, the image is led to co efficient selection, where the images is separated into black and white combination. Here, the black indicates the defect of the tyre and white indicates the normal undefected backdround. More specifically, defective regions in images are regarded as objects, and defective-free regions as background. After this step, here the inverse transform comes, where the black area is inversed into white area and vice versa.

After the completion of First module, the image is led into the second module. In that module, the first step is Guassian filtering, where the processed images are refined and reduce the noise over the images. The reduced noise image is goes to local edge estimation, where the defect marking edge are clipped and processed ,thereby it is led to edge magnitude computation. In this stage, the clipped edges are more refined and the edges are clearly emphasized. The output will show the index, name, type, size, preview , progress, status and predication of tyre. Therefore the tyre defects are known and led to further progress.

This model tends to make everything easier. Moreover, the detection mechanism using the curvlet transform, which ultimately can give greater accuracy of detection. This work would provide practical usefulness to both researchers and practitioners in various industrial fields.

III. *Implementation and Results*

Automatic quality inspection is strongly desired by tyre industry to take the place of the manual inspection. The data is collected by capturing images on the defected tyre with the help of quality manager. The web application was developed using Python and the libarary called Pytorch. Collected data is then uploaded into our web application. In this paper, we use Curvlet transformation strategy for obtaining the Multiscale object representation, which is initialized in network construction.

To reduce the size of the images to be analyzed we need a preprocessing phase, that imported images are clipped into required format, which is already included in our proposed method. As already mentioned, the tyre images are unique and isolated and has some unique ID. These ID are used later for decision making unit. The sample output of our proposed detection method is mentioned below.

Figure 6: Sample Output

This data is then pre-processed and fed into our proposed system, this is where the image goes through further processing using Curvelet Transform, co-efficient selection on the sections on the image that have been transformed, this processed image is the converted and a gausian filter is applied to reduce the noise that might have been generated in previous steps. In order to find defective edges in the tyre, we first have to determine which points belong to the background and which to the foreground. As already mentioned, the curvelet transformation is going to this process. The process is going differenciate the background as black i.e) the defective part and the foreground as white i.e) the undefective part. Due to the pattern of the tires we have to treat each image point differently. Local edge estimation is then carried out on the data which helps highlight the warped aspects of the image. This data is then fed into a suppression algorithm that makes calculating the edges more accurate.

Then the edges are properly outlined and depends on the size, texture, position of the edges, the defects are classified and mentioned in the output. Meanwhile, the edges are clearly analyzed in different modules in our proposed system. After completion of this task, the web application will indicate the defect affected in the tyre and then the tested tyre is led to reprocessing in the manufacturing unit or isolated from the unit, depending upon the percentage of the defect affected in the tyre. Then the next tyre image is imported as the same way to predict the affected tyre is lead to isolation unit or re-processing units which depends on the overall percentage. Under different applications, the curvelet transformation of the image using one or more combination of data augmentation transform can be used to increase the amount of input data. So the data augmentation is done by our proposed transformation scheme. To evaluate the proposed model, we conduct an experiment and show the performance and implementation of our work. Then we figure out the performance, robustness and endurance of our proposed mechanism to other techniques like tyre classification with Django framework, tyre defect detection using X ray technique.

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IV. *Conclusion*

In this paper, we have developed a defect detection system by using curvelet transform techniques to analyze a tyre defects. This model tends to make everything easier. Our proposed work works with overall accuracy of around 91.3% after tested with three more models. This paper explores the solution for the tyre defect detection using edge detection, which has outstanding performance in solving segmentation, tread separation, sidewall and other problems. This work helps the people to improve their standards while manufacturing. Experiments show that the proposed method is applicable to more types of defects compared with traditional methods..

V. *Reference*

[1] Q. Guo, C. Zhang, H. Liu, and X. Zhang, ‘‘Defect detection in tire X-ray images using weighted texture dissimilarity,’’ J. Sensors, vol. 2016, Feb. 2016, Art. no. 4140175. Poverty in India(Economic measures)

[2] Y. Zhang, T. Li, and Q. Li, ‘‘Defect detection for tire laser shearography image using curvelet transform based edge detector,’’Opt.LaserTechnol., vol. 47, pp. 64–71, Apr. 2013

[3] Z. Yan, L. Tao, and L. Qing-Ling, ‘‘Detection of foreign bodies and bubble defects intire radio graphy images based on total variation and edge detection,’’ Chin. Phys. Lett., vol. 30, no. 8, Aug. 2013, Art. no. 084205.

[4] Y. Zhang, D. Lefebvre, Q. Li: Automatic detection of defects in tire radiographic images, IEEE Transactions on Automaton Science and Engineering, Vol.: PP, Issue: 99, pp. 1–9, DOI: 10.1109/TASE.2015.2469594 (2015).

[5] Q. Guo, Z. Wei: Tire defect detection using image component decomposition. Research Journal of Applied Sciences, Engineering and Technology 4(1) 41–44 (2012).

[6] T.Y. Kong, A. Rosenfeld: Topological Algorithms for Digital Image Processing. Elsevier Science, Inc., 1996.

[7] L. Jinping, H. Wendi, H. Yanbin, Y. Jianqin: Crack detection in tread area based on analysis of multi-scale singular area. Communications in Computer and Information Science 547 201–218 (2015).
[8] Y. Xiang, C. Zhang, Q. Guo: A dictionary-based method for tire defect detection. Proceedings of the IEEE International Conference on Information and Automation (ICIA ’14), pp. 519–523, Hailar, China, July 2014..
[9] H. Y. T. Ngan, G. K. H. Pang, and N. H. C. Yung, “Automated fabric defect detection—a review,”Image and Vision Computing, vol.29,no.7,pp.442–458,2011.
[10] A. Kumar, “Computer-vision-based fabric defect detection: a survey,”IEEE Transactions on Industrial Electronics ,vol.55,no. 1,pp.348–363,2008.
[11] A. Latif-Amet, A. Ert¨uz¨un, and A. Erc¸il, “Efficient method for texture defect detection: sub-band domain co-occurrence matrices,”ImageandVisionComputing,vol. 18,no.6,pp.543– 553,2000.
[12] A. Kumar and G. K. H. Pang, “Defect detection in textured materials using optimizedfilters,”IEEETransactionsonSystems, Man,and Cybernetics PartB: Cybernetics,vol.32,no.5,pp.553–570,2002.
[13] T.Liu,Z.Yuan,J.Sunetal.,“Learningtodetectasalientobject,” IEEETransactionsonPatternAnalysisandMachineIntelligence, vol.33,no.2,pp.353–367,2011.
[14] D. R. Martin, C. C. Fowlkes, and J. Malik, “Learning to detect natural image boundaries using local brightness, color, and texture cues,” IEEE Transactions on Pattern Analysis and MachineIntelligence,vol.26,no.5,pp.530–549,2004.
[15] N.˙Imamo˘glu,W.Lin,andY.Fang,“Asaliencydetectionmodel using low-level features based on wavelet transform,” IEEE TransactionsonMultimedia,vol.15,no.1,pp. 96–105,2013