Surface Inspection of Carry Side of Conveyor belts using Open CV and Machine Vision algorithms

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Abstract— In the Mining Industry, Conveyors are extensively used to carry various raw materials, coal and fluxes from remote mine faces to the stock yards/processing plants and other upstream process. These conveyors made of rubber or steel corded rubbers are extremely critical for plant operations and any breaks in the belts can require several days for repair. An early warning system is being devised to detect surface erosions, abrasion and tears in their nascent stages so that by splicing or vulcanization repairs can be effected immediately and life of the belt can be extended .This paper presents an efficient method to use Open CV algorithms on appropriately illuminated images from an area scan camera or any high resolution cameras to contrast, texturize and detect various categories of defects. Experimental evaluation shows that for a standard severity index Gaussian and Laplacian operations provide the desired results and least false positives among all techniques evaluated. The system software then facilitates manual defect categorization and classification for subsequent Automatic Defect Detection.

Key words: Conveyor surface defects, carry side, Open CV, SIFT, Laplacian, Machine Vision, blurring, de-texturization, edge detection, Direct Cosine Transform, Classification

I. INTRODUCTION

In the Mining Industry various raw materials, ores and over burden are brought to the stock yards or waste pits using over land conveyors. These conveyors can be of various types and can run up-to several kilometers carrying several million tons of materials during the year. This paper discusses the defect detection and classification of belts which are of Rubber type and used for conveying ores and fines .Typical life of such a belt can range up-to 2-4 years depending on the materials carried, type of belt and the health of the driving rollers. Belts are made of rubber, PVC, Nylon, neoprene etc. covering an inner carcass, which may also be steel corded for providing mechanical strength. Defects on the belt may be due to regular abrasions from the materials conveyed or by any foreign particle which may penetrates the belt and cause longitudinal tears driven by the rollers underneath. Any tear to the belt left unattended decreases the life span of the belt and in case of belt snaps or breaks it takes several hours to days to splice the broken ends together. This paper presents a system which uses machine vision to inspect the carry (top) surface of the belt and detects developing defects such as tears and abrasions at a nascent stage to trigger prompt repairs and thus increasing the productive life and throughput of the belt.

II. TYPE OF CONVEYOR BELTS AND COMMON DEFECTS

A. Conveyor belts:-

Conveyor belts which are used to carry ores and raw materials are made out of various materials such as Rubber, Nylon, Neoprene which is stretched over a carcass generally containing or embedded with steel cords to provide additional mechanical re-enforcement. (See Fig.1.0 A and B – Typical Rubber Carcass and Steel cord carcass belts)

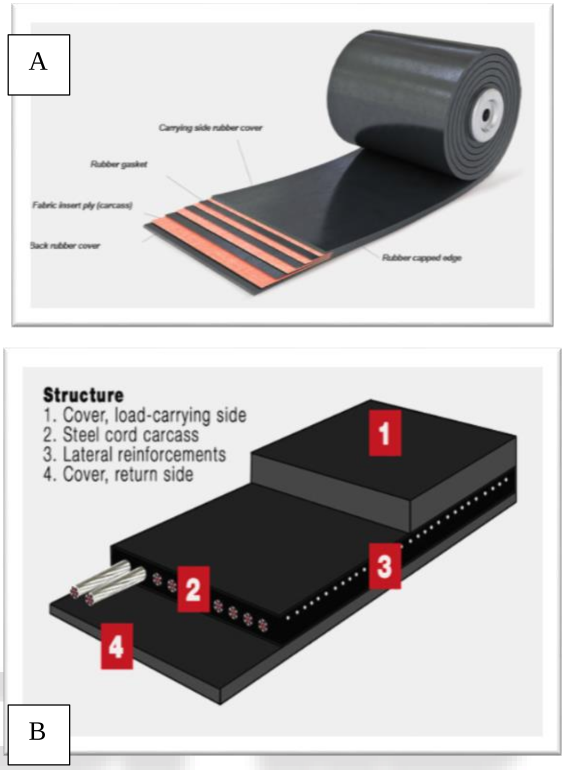

Fig. 1: Examples of Conveyor Belts

These Belts usually have along life but defects and tears due to mis-aligned rollers on the bottom side also called drive side or when sharp shards of ores falling from chutes penetrate the top surface and longitudinal tear develops when the sharp knife edge gets wedged against a roller while the belt moves across it.

Defects such as cracks and tears may also develop due to weathering of the belt, abrasion, erosion and gouging by falling materials and many other reasons.

Once the belt snaps it is spliced/joined together applying heat and pressure similar to vulcanization process, [7] called endless splicing and metallic/nonmetallic mechanical fasteners and various other adhesive methods depending on the type, location, severity etc.

These splices also get abraded and deteriorate over time and it is required to inspect the belt regularly to ensure that belt failures are avoided as they lead to throughput and productivity losses for obvious reasons.

B. Common Conveyor Defect Detection and monitoring systems:-

Various OEM’s have provided Belt monitoring and early defect detection systems.Some systems are vision based while others are a combination of vision and Electro mechanical sensing systems. Fig(2.0 B)[6]

Vision based systems are not popular for all applications as due to weathering , material carried and sludge adhereing to carry surface during rains, colourization and pigmentation of th ebelt occurs which may provide false positive errors to any image based system.(Fig.2.0 A)[6][7][14]

Also the drive side or bottom of the belt develops faults by continual friction damage from mis aligned rollers which remain invisible from the carry side.

Some steel cord belt manufacturers use eddy current sensing to detect the integrity of the steel cords embedded inside the belts by placing eddy current sensors and monitoring trend of the flux generated as the belt traverses over the sensors.(Fig. 2.0 D)[7]

Infra Red meshes or mechanical sensors underneath belt are deployed to detect punctures and tears which cause materials to fall underneath and trigger the sensors (Fig 2.0 C)[9]

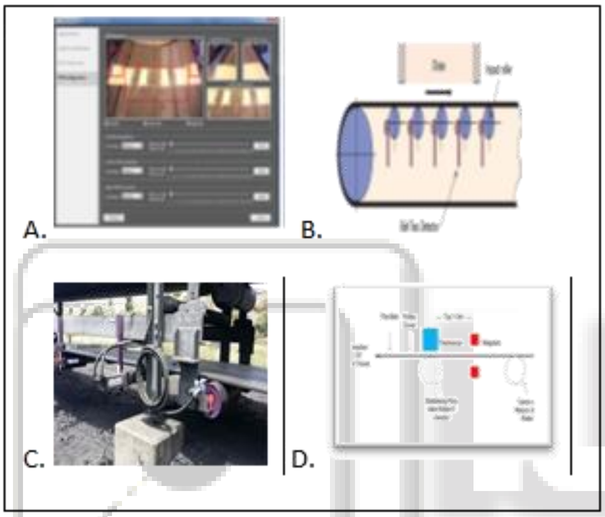

Fig. 2: Types of Conveyor Defect Detection Systems available.

C. Common Defects in Conveyor Belts:-

Defects on the belts depend on the type of materials it is carrying, if the material has rough edges, if it is being dropped from a high chute, portion of the belt exposed to the weather etc. Also the undersides of the belts are affected if the driving rollers cause abrasions due to splintering or mis-alignment. Defects by the drive rollers affect the underside or drive side of the belt and may be marginally visible as edge tears on the carry side. Longitudinal tears develop when sharp materials pierce through the belt and get wedged against the rollers. The belt moving against the wedged sharp material gets split right across.(Fig. 3.0)

Other defects which develop gradually are surface erosion of the belt by carrying abrasive materials and cracks which appear due to weathering (Fig.7.0). Air pockets may develop within the carcass of the belt and are very difficult to detect by conventional imaging techniques as on the surface they appear as slight ballooning only. (Fig.6.0)

The joints where sections of belts have been fused or spliced together get weakened over time. The mechanical fasteners may shear off or develop gaps due to the longitudinal stresses while the vulcanized sections after seamless or endless splicing may tear off due to wearing of the adhesive bonds.(Fig 4.0) However these become difficult to detect as they happen gradually while mechanical fasteners can be monitored for developing defects.(Fig.6.0).

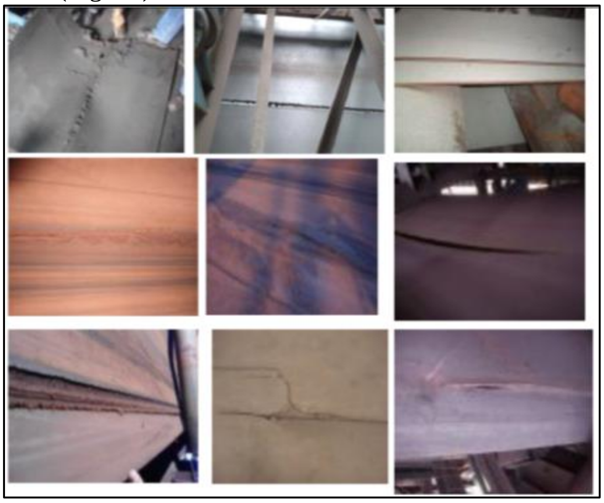

Fig. 3: Examples of Longitudinal Belt tears

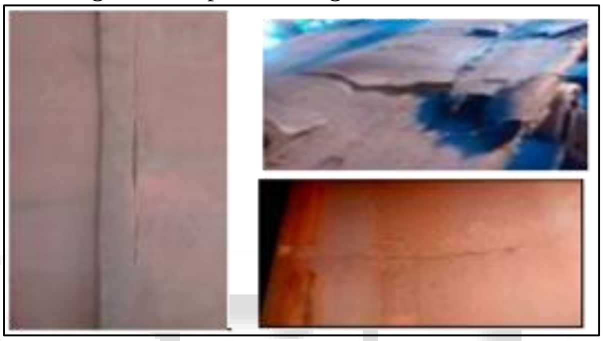

Fig. 4: Examples of Rubber Separation at Joint and Joint Failures

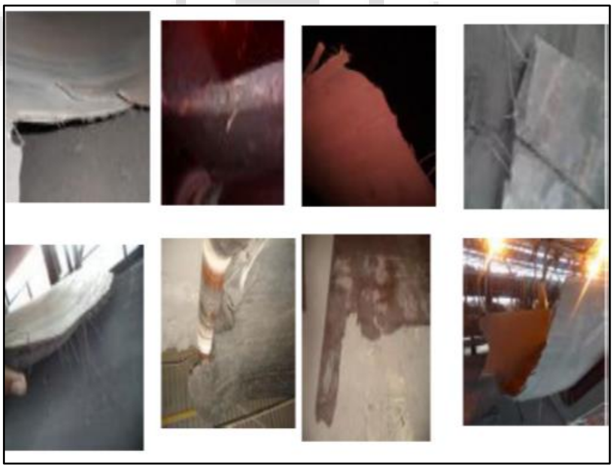

Fig. 5: Snapping and Shearing of Belts

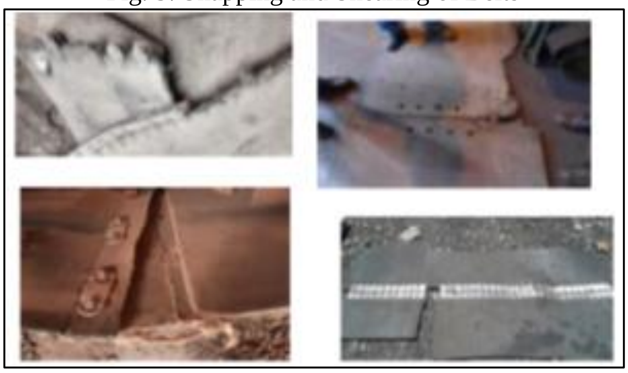

Fig. 6: Clip joint failures, air pockets and edge tear

Fig. 7: Cord Breakage, Ageing/Thickening and Belt folding

III. DEFECT DETECTION USING MACHINE VISION

Open CV[4][5] (Open Source Computer Vision) originally developed by Intel is a library of programming functions mainly aimed at real-time computer vision.IT can be used to detect objects, shades, textures, edges, colours etc. Various algorithms incorporated in this library makes it a very versatile and easy system to detect visible surface defects and blemishes and these can then be classified ,indexed to make the algorithm more robust and intelligent over subsequent iterations.[11][12][14]

In this paper, Continues Images of a conveyor belt, acquired at a high resolution, high frame rate by a CCD camera, illuminated by structured lightening is acquired. Using various software's and algorithms the surface defects are identified and categorized by both manual intervention and automatically by employing a heuristic classifier approach.

A. System Overview

To Acquire High resolution images at high frame rate an experimental set up was created to remove variability in the image acquisition process for the purpose of testing the various algorithms. This was achieved by erecting a fixed camera and lens mounting arrangement in front of the conveyor belt near the take up pulley where the belt is presented as a vertical and flat surface to the camera.(See Fig.8.0) Structured light source was provided using metal halide lamps nearly perpendicular to the surface of the belt to ensure isotropic luminance for the surface. The best results can be obtained when the uniformity ratio of the delivered light is nearest to unity. Also it is theoretically desirable that surface have Lambertian reflectance properties, practically this is not possible to achieve and image processing algorithms have to be used to compensate for the gradients etc. [13]

An air knife or air curtain was installed to ensure that dust and muck from the surface of the conveyor would not get deposited on the lens leading to erroneous results. The camera is connected to the Image acquisition Workstation over OFC (Optical Fiber Cable) and terminates into a Gigabit Frame Grabber card installed in the Image Acquisition Workstation. (See Fig. 8.0)

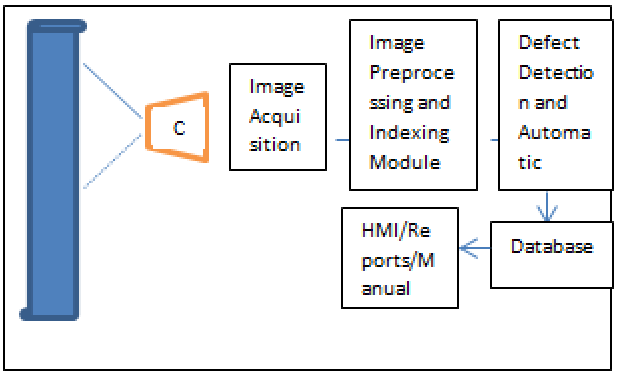

Fig. 8: Functional Block Diagram of the System

Various OpenCV algorithms are used to preprocess the images, sort and index it for presentation in an HMI after rendering the defects. These are described in later sections of this paper. The Image acquisition Workstation also hosts a webserver and database. HMI (Human Machine Interfaces) have been developed which allows expert users to view the acquired images and detected defects using their web browser over the Local Area Network. Provision of obtaining real time speed of the conveyor is kept obtaining speed from the drive SCADA (Supervisory Control and Data acquisition System) or integrating a hollow shaft encoder on the drive take up pulley.

It is envisaged that correlating the drive speed to the camera shutter will enable discrete sequence of the belt to be captured [10].Also using a visible identifying mark on the belt surface as a reference frame; the subsequent frames acquired from the Camera could be sequenced. However in the scope of this paper experiments with using Machine vision algorithms such as SIFT [1] has been conducted to make the system able to acquire and sequence the image frames contiguously, independent of the drive speed.

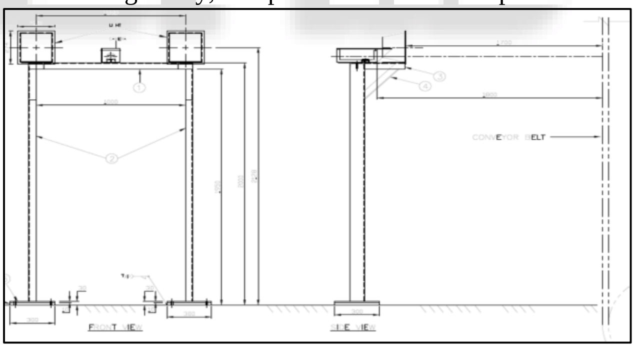

Fig. 9: Mounting arrangements of Camera and Light in front of the conveyor

B. Methods and Algorithms for Defect Detection

The frames acquired from the camera are at the rate of about 70 frames per second [10]. Every 35th frame is grabbed and used for further processing. The speed of the conveyor selected for the experiment is approximately 2.2 meters per second and length is about 1500 meters. The camera and vari -focal Lens has been arranged such that the vertical edges of the image and the belt overlap exactly. The upper and bottom 10% of the image by pixel size is cropped to remove the blurring effect and possible inaccuracies from luminance variations due to angle of incidence. Therefore the region of interest remains 80% of the frame.

OpenCV originally developed by Intel Corporation is an open source library for real time machine vision applications [4][5]. In this paper various algorithms of OPENCV have been used to detect and isolate visible defects on the surface of the conveyor. Visual C++ 2012 has been used for this while database is MySQL and web based HMI screens have been developed in C#.Net 2012

Initially using OpenCV function the raw image is converted into grayscale. As seen is Figure 10. a lot of striations and scales are visible on the surface of the belt. Using further algorithms to identify defect may lead to these striations also being detected as defects leading to false positive results, therefore a blurring technique is required to smoothen the image to reduce the textural effect while keeping the edges and suspected defects in sharp contrast. Various low pass filters and High Pass filters are used to achieve this. Converting the image into its negative also creates good contrast between the textural variations across the belt.Fig.10 A is the cropped Raw image while Fig.10B is its negative.

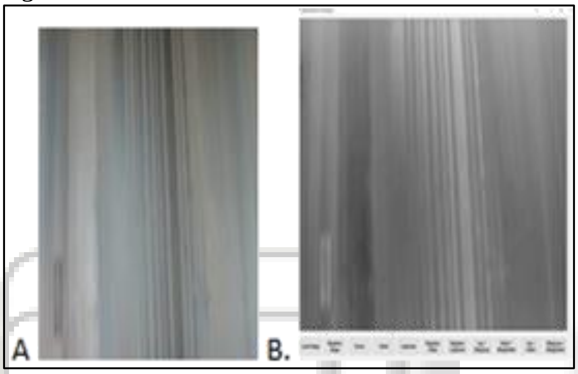

Fig. 10A: Raw image of the conveyor belt Fig. 10B: Negative of the Raw image

Example of 2d convolution or averaging filter - A kernel or a central pixel and pixels below it are mapped in a matrix and averaged. The average values are then used to replace the central pixel. See equation 1.1 for a 2d convolution filter.

$$K = \frac{1}{25}\begin{bmatrix}1 & 1 & 1 & 1 & 1\\ 1 & 1 & 1 & 1 & 1\\ 1 & 1 & 1 & 1 & 1\\ 1 & 1 & 1 & 1 & 1\\ 1 & 1 & 1 & 1 & 1\end{bmatrix} \quad (1.1)$$

Hence smoothening techniques such as Averaging Filter (Fig.11A.), Gaussian Blurring (Fig.11B), Bilateral Filter (Fig.11C) and Median Blurring (Fig.11D.) exist and these can be utilized to smoothen the image, keeping the edges in contrast.During the experiment various smoothening and blurring techniques were applied on the image to select the operation which would preserve the contrast between edges while blurring the textural variations of the belt. (See Fig. 12)

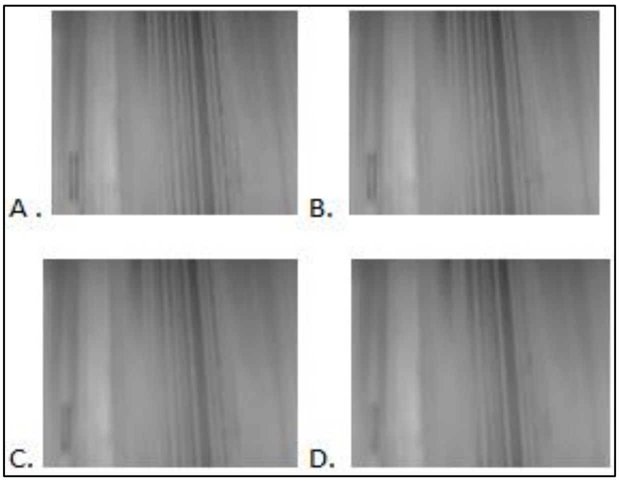

Fig. 11: Various Types of Smoothening Techniques on source image

After experiment over various frames containing defect and those without, it was determined that eventually images smoothened using 2d convolution or averaging filter gave the best results(least false positives and best de texturing) during subsequent stages of processing and defect detection.[4][5]

C. Detection of Edges

Once the images are smoothened and de texturized it is required to detect the edges of the defective and non-defective areas on the surface of the belt. This can be done by detecting the contrast or pixel intensity and variations between gouges, cuts and cracks which are freshly developed, relative to the weathered and abraded surface of the remainder of the belt image. There are several edge detection techniques which are available in OpenCV library such as Laplacian, Canny and Sobel among others [4][5]. Also these operations can be carried out on the negative of the raw image to obtain different pixel intensity values.

One popular edge detection technique developed by John F Canny [15] uses a multi stage algorithm to detect the edges. In brief noise reduction of the image is done, and then the intensity of the image is found out. After getting gradient magnitude and direction non maximum valued pixels in the direction of the gradient are suppressed or set to 0 and so on. Finally Hysteresis thresholding algorithm decides which true edges are if intensity is over a maximum value or by checking linkages of pixels with intensity between the maximum value and a specified minimum value and so on. [4][5]

The results obtained from Canny edge detection on the Conveyor image is shown in Fig.13.Due to the striations, discolorations , shading and pigmentation which develops over the conveyor surface after a period of time intensity gradients could not be detected satisfactorily and this technique was rejected.[11][12].

Fig. 12: Canny Edge Detection of Conveyor image

Similarly Sobel and Laplacian techniques were tried out. Sobel edge detection is based on the fact that in the edge area the pixel intensity shows a "jump" or a high variation of intensity. Getting the first derivative of the intensity, we observed that an edge is characterized by a maximum, as it can be seen in the figure 14.

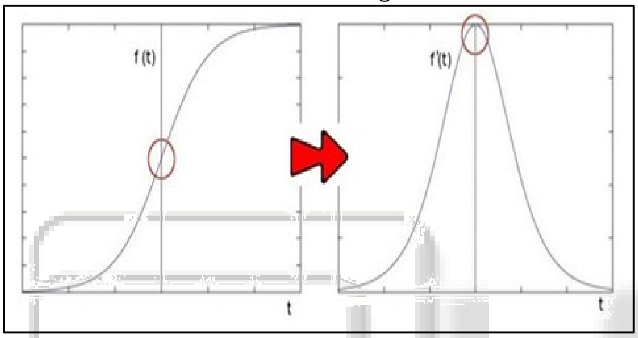

Fig. 14: Sobel Edge Detection from first derivative of intensity

Laplacian on the other hand uses 2nd derivative to detect the edges. Derivatives for the 2 dimensional images are taken in both 'X' and 'Y' directions. (See Fig.15)

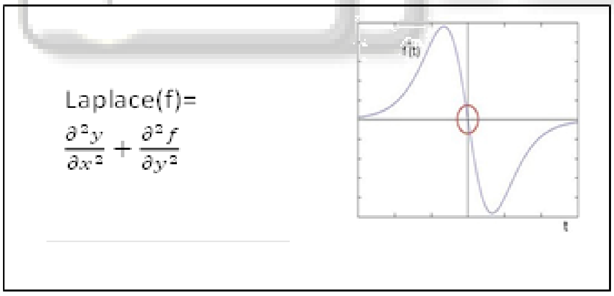

Fig. 15: Laplace Edge Detection from 2nd derivative

Laplacian and Sobel Operators were applied on the conveyor image with 2d Averaging filter. Fig 16 A. Laplacian and Fig 16 B. Sobel,. The same techniques were also applied on the negatives of the raw image to observe the edge detections on the belt surface. (Fig. 16 C. Laplacian of Negative image and Fig.16D. Sobel detection of the negative image)

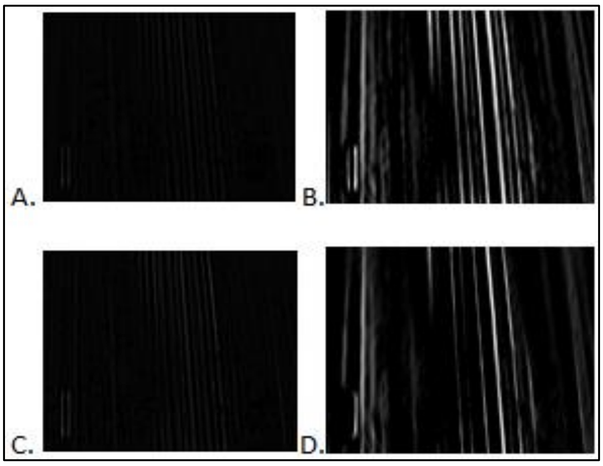

Fig. 16: Laplacian and Sobel edge detections of the image and its negative

Similarly Laplacian and Sobel operations were performed on the conveyor image with Bilateral, Median and Gaussian filters with results as depicted below in Fig.17.[4][5]

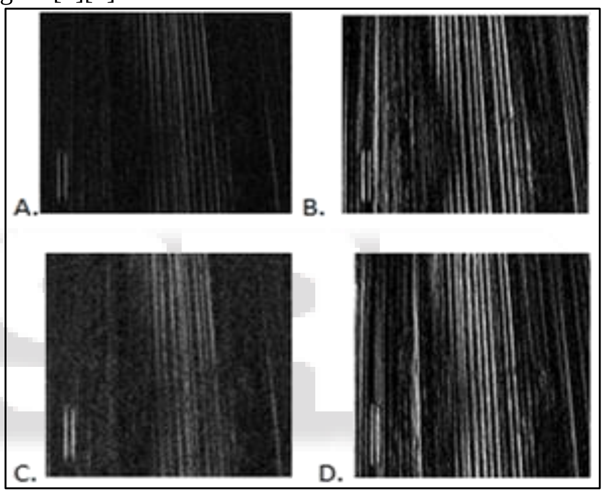

Fig. 17: Laplacian and Sobel Edge detection with Bilateral, Gauss and Median Filtering

The Fig. 17A shows result of Laplacian operation and Bilateral filtering, Fig.17B is Sobel operation on bilateral filtering. Similarly Fig.17 C and D are Gaussian Filtering and Fig.17E and F are median filtering respectively. The experiments proved conclusively that Sobel operations were far more sensitive to gradient changes and detected far more edges which would lead to more false positive results. Laplacian operations over 2d convolution or averaging filter gave better results as mentioned earlier.[8][11][12]

During the experimentation averaging or superimposition of Laplacian operation on the image with its own negative was also carried out with the results presented below in Fig 18.A to D. However when these were used as source image for defect detection the results were statistically inconclusive and these techniques were not used during further processing.

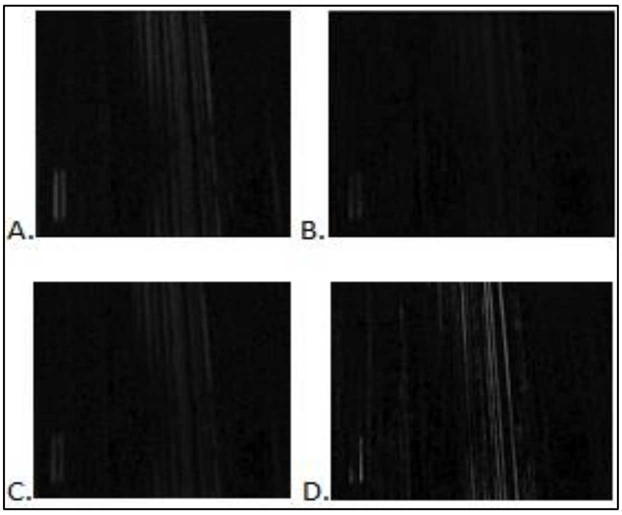

Fig. 18: Laplacian+ Negative Laplacian image with A. Averaging, B. Bilateral, C. Median and D. Gaussian filters

D. Defect Detection and Identification of Region of Interest:

After edge detection is done the system then draws a rectangle around the Region of interest which is the suspected area with defect [8]. These are validated manually and categorized as defect types (example - Edge Tear, Longitudinal tear, Air pockets, Splice/joints, rubber separation etc.) as mentioned earlier, location of the defect (left, right or center of belt) and its Criticality from 1 to 5 where 1 is minor and 5 needs immediate attention and repair. The image on which the defect has been stored is also saved in the classifier database and in the subsequent iterations the acquired images are checked against this defect for automatic classification before being presented for manual validation.

For Defect detection Discrete Cosine Transform algorithm [2][3] has been selected as it is a well-known algorithm and known to give good results for textural analysis. DCT analysis of each non overlapping region of the image is done for detecting possible defects.

(1.2)

$$DCT(i,j) = \frac{1}{\sqrt{2N}} C(i)C(j) \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} pixel(x,y) COS[\frac{(2x+1)i\pi}{2N} COS\left[\frac{(2y+1)j\pi}{2N}\right]$$

C(x) $=\frac{1}{\sqrt{2}}$ $if\ xis\ 0, else\ 1\ if\ x > 0$

This is achieved by computing energy DCT of gray profile of the image. The resulting energy matrix has been broken into 10 X 10 blocks [3]. The sum of each block is averaged across the block and an energy matrix is developed. Multivariate method is used to locate defective blocks and finally using a severity threshold is used to isolate the defects. It was found that computing the defects using a severity value of 5 was optimal in terms of processing speed reduction in false positive defects.

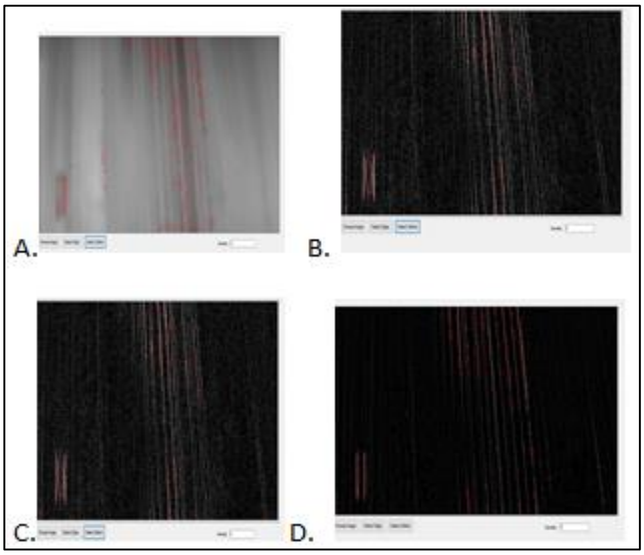

Fig. 19: Defect Detection performed on A. Raw image with 2d Averaging , B. Laplacian Transform on raw image, C. Laplacian transform on negative of image and D. Laplacian with Averaging filter on raw image

The results show that best contrasts and de texturization and lowest false positives have been achieved on applying Laplacian transform and averaging filter on the image.(See fig 19.D).

An accuracy of 76 % was achieved by using this method .The formula used to determine accuracy was:

(1.3) $$Accuracy = \frac{(True\ Defects + True\ Non\ Defects)}{True\ Defects + True\ Non\ Defects + False\ Defects + False\ Non\ Defects)}$$

Other operators had accuracy less than 50 %.

IV. Conclusion and Way Forward

As this system is in an experimental stage it is easy to deal with discrete frames which can be dealt with individually for the scope of the paper. Practically it is required to extract contiguous frames from the live video of the conveyor, process it and display the result in an user friendly HMI [14]. Another practical requirement is to track and compare the progress of any defect which has been detected at an nascent stage. For this experiment is being done to use techniques like SIFT (Scale Invariant Feature Transform) developed by D. Lowe University of Columbia [1] .A unique image frame with any existing prominent feature (Belts have visible seams where they are spliced or joined) will be marked as a reference frame and the subsequent frames will be sequenced accordingly for tracking location of defect and comparison between images of the same section at later times to check for progression of defect etc.

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