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Autonomous Rail Track Inspection using Vision Based System

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Abstract- *This paper proposes a rail track inspection technique using automated video analysis. This system is aimed to replace manual visual checks performed by the railway engineers for track inspection. We suggest a combination of image processing and analysis methods to achieve high performance automated rail track inspection. This paper addresses the problem of finding missing clips and finding blue clips which have been recently replaced in place of damaged clips. The experimental results show high performance in machine vision based inspection on a large sample of real train video.*

Keywords: *Image processing, rail track inspection.*

I INTRODUCTION

Safety in railways is one of the key issues for public transportation companies and a fast and efficient inspection system is important to ensure the safety of railways. Traditional rail inspection methods include *destructive techniques*, such as coring, and *non-destructive techniques*, such as hammer sounding. But these methods can just "cover limited area and have limited effectiveness in identifying possible sites of deterioration" (Delatte et al., 2003). Further non-destructive evaluation techniques for rail inspection have been recently developed. These include visual inspection, ground penetrating radar (GPR), infrared, X-ray, laser light, diagnostic train, magnetic methods, impact-echo, spectral analysis of surface waves (SASW) and impulse-response.

Only during the last five years, video analysis for rail inspection at a large scale has become a possibility. Since image processing is a computationally expensive task, high-speed data processors are needed for video analysis (where a video can contain several thousand images). A lot of the research on the application of image analysis to railway surveillance tasks is only now starting or is in its infancy. Much less has been done in the area of machine vision for rail track inspection. Studies on the collection of videos for railway inspection through manual observation have been carried only recently by some academic/industry partnerships in Canada, USA, Netherlands and Japan. Most of this work is related to tunnel inspection through video logging (Yarza, 2003), surveillance applications (Foresti and Regazzoni, 2001) or understanding human judgment through eye tracking of railway drivers (Itoh *et al.*, 2000). Similarly, tunnel inspection is carried out as a video logging project in most countries recently where the recorded video is viewed by a human expert manually to make decisions. The automated decision making through image analysis is still lacking.

Takeshita (1995) and Bryan (1999) proposed a method for measuring track irregularities using a passenger car instead of using an inspection car. At present the train inspection systems are typically used to measure rail profile (Magnus, 1995 and Bachinsky, 1995), contact wire position and wear (Gigch et al., 1991). In addition, there are train-based inspection systems that currently measure those aspects of the rail track that are easy to estimate automatically such as wheel inspection, pantograph checking, locked wheel detection, brake pad thickness measurement, overheating of the breaking system, train fire detection and automatic train tail sign recognition. However, no such system inspects any surface features on the rail track.

In this paper we propose an automated rail track inspection system for finding clips on the rail-track. The condition of the track is recorded using a video camera. Our methodology is described in the next section which details the image processing operations involved in video analysis for rail track inspection. Our results show that highly robust rail inspection is possible through our image analysis method as discussed in section 3.

II IMAGE PRE-PROCESSING

Our objective is to automatically find clips in video sequences and thereafter recognise whether they are broken and if they are new or old as indicated by their colour. Metal clips hold the rail track to the sleepers on the ground. We need to find the clips and locate their position. It is reasonable to assume that some of the clips may be broken or missing (because of excessive strain on them as the train moves on the track) which may lead to the track failure and an accident. Identification of missing clips is critical for avoiding accidents. The clips are also found in different colours, some blue (newly installed clips) and some grey (old ones). So if we could find out if a clip is old or not by colour analysis of the video, it will be great help to engineers who are in charge of maintenance and replacement of the clips. They will know exactly which clip has just been changed and the condition of the track in different areas. The main image pre-processing steps in the recognition of clips include smoothing, edge detection, and short line removal. These are described in brief below. Only after this pre-processing it is possible to apply further algorithms that find clips and output their properties.

A. Gaussian Smoothing

Gaussian smoothing is used to reduce noise pixels from the image without interfering with important features in the original image. We use a mask sized 3*3 with neighbourhood averaging.

B. Edge Detection

Canny [4] determined edges through an optimization process and proposed an approximation to the optimal detector as the maxima of gradient magnitude of a Gaussian-smoothed image.

C. Short line removal

All the boundaries between two dissimilar regions in an image are represented as a one-pixel width line after Canny edge detection. As we are only concerned with track and clips, so we do not need to analysis all the edges. As a result, some edges that is shorter than a threshold in the edge-detected image should be considered as unimportant features and be removed. The idea of doing so is to track all the edges in this edge-detected image one by one; record the length of each edge; and remove the ones with the length shorter than a given threshold.

III EXPERIMENTAL RESULTS

In this section we present the experimental results of finding all clips, finding only blue clips and then missing clips. All experiments were conducted on rail video provided by Corus. The complete video is of 42 minutes and 20 seconds in duration and is taken with the Heathrow Express train journey between London and Heathrow airport. A video camera is mounted next to the wheel of the train with a directed lighting source. We sub-sampled the video since in some frames the clips and rail track are not properly illuminated due to ambient lighting interfering with the lighting source. This happens mostly in open stretches of outdoor environment. In this video, the outdoor railway track has little bolts instead of clips to hold sleepers and most repairs are visible in the stretch within the tunnel. Hence for our study we use tunnel part of the video. Altogether 7 short video sequences that are one to one and a half minutes long were cut from the original video to test. Table 1 shows the duration of the videos in seconds and the number of frames analysed. Each image frame is of size 384x288 pixels.

In the next three sections we present our experimental results. The results are shown with how well the automated image analysis method is able to detect clips of interest and catalogue their properties. The accuracy of the system is tested against manual ground-truth labels provided by a human rail track engineer from Corus Rail. The manual labeling is a tedious process and it was recorded for each image frame.

Table 1. Details of the 7 videos used for testing

Video	Tunnel / Outdoor	Duration	Frames
V01	Tunnel	80	2000
V02	Tunnel	60	1500
V03	Tunnel	80	2000
V04	Tunnel	55	1375
V05	Tunnel	80	2000
V06	Tunnel	80	2000
V07	Tunnel	80	2000

A. Finding Clips

After short line removal, only the important edges are left in the image (only wheel, tracks and clips). As all the clips appear in a well-defined area (window of interest), we could just focus on this area. Clips are recognised by placing a set of image windows along the lines representing the track that have a high possibility of containing clips. Thereafter, we count the number of edge pixels in each window. This gives us the density of edges in each window. After plotting edge density in each window vs. the window numbers, the peak value can be determined. This peak represents the position of the clip. When the peak value is smaller than a given threshold, the window will not be considered as containing a clip, but some noise. When there are two peak values and both of them are bigger than a set threshold, the frame will be labelled as containing two clips.

Table 2. Results on finding clips

Videos	***Frames***	***Clips In Video***	***Clips Missed***	***Accuracy***
V01	2000	2303	36	96.9%
V02	1500	2106	62	94.1%
V03	2000	2750	48	96.5%
V04	1375	1802	97	89.2%
V05	2000	2533	28	97.8%
V06	2000	2675	64	95.2%
V07	2000	3070	42	97.3%

In Table 2 we show the results of how accurately our system is able to find clips in the first place. On average our system is 95.3% accurate in recognizing clips. Some of the clips are not recognized because the edge detection process finds them as disconnected pixels which are impossible to link together as a cohesive clip.

B. Finding Blue clips

To find blue clips, we perform colour analysis on the pixels of the window containing the clip. If we focus only on the distribution of three primary colours in one window (red green and blue), we can see when the colour of the clip found is grey, the distribution of three colours in the box will be very similar. However, if the clip in the window is of the colour blue, then the tail of the blue distribution will be thicker and stretch for much longer- the density of blue colour component for high intensity pixels will be more than of the two other colours. This is shown for grey and blue clips are shown in Fig.1.

Table 3 shows the accuracy with which blue clips can be accurately recognized in different videos. The accuracy varies considerably since the clips are not binary in colour (blue or grey)- instead there are different shades of grey and blue and there is some discrepancy between manual labeling (what the human eye perceives to be blue) as opposed to the image analysis output. On the whole the system is on average 86.5% accurate in recognizing blue clips which is of use to track inspectors in identifying those regions of the track that have been recently modified (a correlation between the image frames and GPS data/ and or analysis of other landmark features can pinpoint the location of the features of interest as visible in the video). Table 4 shows that the system is much more accurate in recognizing grey clips (95.3% accurate on average).

Table 3. Results on finding blue clips

Videos	*Frames*	*Blue Clips Identified*	*Accuracy*
V01	2000	21/28	75.0%
V02	1500	245/273	89.7%
V03	2000	1827/1940	94.2%
V04	1375	498/570	87.4%
V05	2000	181/186	97.3%
V06	2000	73/97	75.3%
V07	2000	336/387	86.8%

Table 4. Results on finding grey clips

Videos	*Frames*	*Grey Clips Identified*	*Accuracy*
V01	2000	2264/2275	99.5%
V02	1500	1810/1833	98.7%
V03	2000	662/810	81.7%
V04	1375	1176/1232	95.5%
V05	2000	2280/2347	97.1%
V06	2000	2556/2578	99.1%
V07	2000	2561/2683	95.5%

C. Finding Missing clips

The original video that we have does not have any missing clips. Therefore, to test the detection of missing clips, we manually removed clips. The procedure to remove clips can be described as follows: if a clip is found at position P in frame A, find another frame B with no clips at position P. Cut a little window of position P from frame B and cover the original area in frame A. Then, we perform Gaussian smoothing on the boundary of the missing clip area in the revised frame A in order to blend the patch made with its surroundings. On average 10% of the clips were removed in all videos. An example with missing clip is shown in Fig.2.

Table 5 shows the results of finding missing clips. The image analysis algorithm finds missing clips by analyzing the contents of the image region next to the rail track similar to how we found clips in the first place. The results show that on average the system is 84.7% accurate in finding missing clips.

Table 5. Results on finding missing clips

Videos	*Frames*	*Missing Clips Identified*	*Accuracy*
V01	2000	179/200	89.5%
V02	1500	131/150	87.3%
V03	2000	182/200	91.0%
V04	1375	119/138	86.2%
V05	2000	174/200	87.0%
V06	2000	157/200	78.5%
V07	2000	148/200	74.0%

IV SUMMARY AND CONCLUSIONS

This study suggests that the future of railway inspection lies in developing automated rather than manual methods. It has been suggested by latest research that modern railway tracks will use image analysis as a core method of inspection in the near future (Esveld, 2001), especially as it becomes possible to handle large amounts of data in real-time. Image analysis offers superior choice compared to other sensors in its ability to get high-resolution images. Also image analysis offers flexibility in analysis where difficult images can be classified by a human expert and the remainder automatically, whereas other sensors must be analyzed by the computer in full. In addition, image analysis algorithms are easier to develop and understand given that we can visually interpret images as humans, but we cannot do the same for other forms of signals. Our experimental results have shown that the automated approach has much promise and the use of image analysis in railway inspection will lead to improved rail safety and much cheaper mode of operation. Our current work on this project with samples of the videos are available at: http://www.railtrackinspection.com

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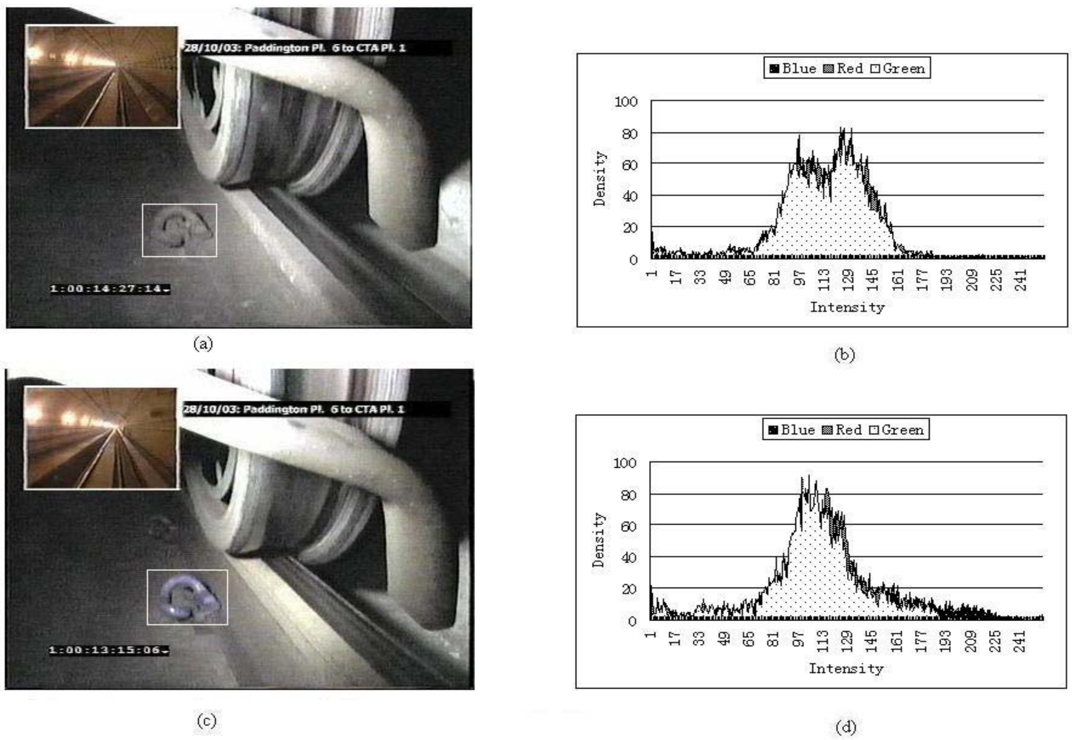

Fig.1. (a) Image with grey clip in it (b) Plot of three-colour distribution of the box in (a)
(c) Image with blue clip in it (d) Plot of three-colour distribution of the box in (b)

(a) (b) (c)

Fig.2. (a) Frame A has a clip at position P, (b) Frame B has no clip at position P, (c) Frame A with position P covered by Frame B