Detection of Mud Pumping using Computer Vision and Track Irregularity

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1. INTRODUCTION

Railway is one of the major lifelines of a country's economy making it easy to transport humans, goods, and services. One of the key components of its infrastructure is the rail track. Currently, the identification of damages on railtrack is carried out on a timely basis by manual inspection, which is susceptible to human error. In the category of rail damage, mud pumping, shown in Figure 1, is one of the most prevalent conditions that needs to be flagged as soon as possible. Under the influence of heavy cyclic loading, mud flows to the top of the railtrack, leading to the settlement of tracks. Delay in identification could lead to the substantiation of the maintenance work. In this paper, a combination of vision-based indirect measurement of the movement of ballast using time-series of images and high-track irregularity to detect mud pumping locations is proposed.

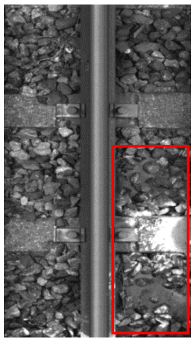
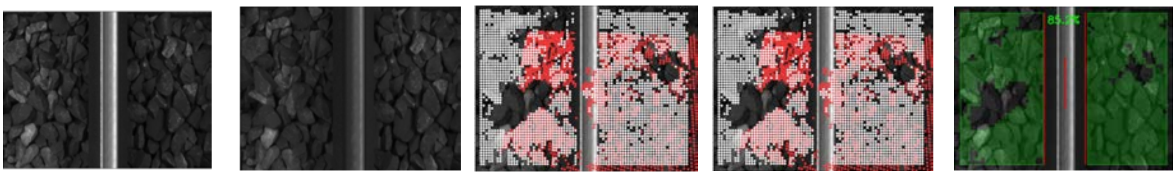


Figure 1: Rail track with the red square indicating mud pumping

2. INDIRECT MEASUREMENT OF BALLAST USING IMAGE SIMILARITY

Liu et.al (2019) [1] observed that the movement of individual ballast particles at mud pumping sections were larger than at other locations. In the proposed methodology, this idea is applied on a macro level and the movement of ballast within consecutive sleepers for a year [Aug 2021- Jul 2022] was calculated. Images of a railwayline in Japan were used to calculate the movement of ballast. The dataset included top-view images of the railtrack for 12km, with each image being 5m long at a resolution of 5000 x 1024 pixels. Images of ballast between sleepers were extracted by identifying the locations of sleepers. At each location, images were obtained 9 times in the one-year period. Similarity of images taken at consecutive time instances was quantified. Thus, 8 image similarity values were examined for each location. In order to carry out image similarity quantification, the following steps were performed.

1) Using LoFTR algorithm [2], deep-learning based feature matching algorithm, common feature points between the two images were extracted.
2) Mis-matches were removed by identifying points which have displaced from the initial position by setting a threshold on the maximum allowed movement. To increase the number of feature points identified, an iteration of homography transformation is applied to the images, and are followed by feature matching and removing mis-matching.
3) The location of rail is identified in the image is identified and the feature points corresponding to this location is removed.
4) Percentage similarity is calculated by calculating the ratio of the area of the image which contains feature points to the total area.



a) Sep. 2021 *b) Oct. 2021* *c) Feature points, Sep. 2021* *d) Feature points, Oct. 2021* *e) Sep 2021 with the image similarity value*

Figure 2: Feature Matches detection between images of ballast at the same location taken between consecutive months.

Figure 2a) is an image of ballast taken on Sep. 2021, while Figure 2b) was taken on Oct. 2021. Figures 2c) and 2d) indicate the feature points obtained after step 2 at this location. Figure 2e) has two images superimposed on top of one another. The image taken on Sept 2021 is superimposed with the green color indicating the locations where the ballast has not moved. According to the feature matching, 85.2% of the total ballast area is not moved. By applying the above methodology, the spatial-temporal variation of image

Keywords: Mud Pumping, Image Similarity, Feature Matching, Track Irregularity
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similarity of ballast was obtained.

3.COMBINING IMAGE SIMILARITY WITH TRACK IRREGULARITY

4m-chord track irregularity values were used to calculate the locations of mud pumping. The data was obtained 110 times over the year, with a pitch of ¼ m. The minimum track irregularity value for every 10m stretch was calculated and its spatial and temporal variation is investigated. Figure 3 shows the variation of minimum track irregularity at a 10m stretch from May 2021 to Aug 2022.

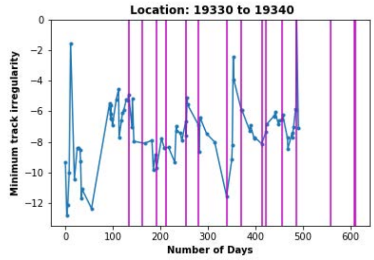

Figure 3: Temporal variation of minimum value of track irregularity at a 10m

4. RESULTS AND CONCLUSION

The mud pumping locations are identified as location with track irregularity value less than -6mm. Similarly, locations with the image similarity values less than 40% was used to identify the presence of mud pumping. Figure 4 denotes the image similarity quantification results at a) mud pumping location (23.8% < 40%) and b) non-mud pumping location (76.7%> 40%). In order to remove the influence of low similarity of images due to maintenance work, more than 2 consecutive low similarity values were used to detect the occurrence of mud pumping. In Figure 6, locations between 19334.68 and 19331.43 correspond to mud pumping.

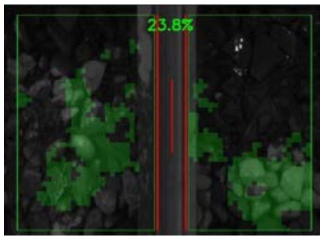

Figure 4: Image similarity at a mud pumping location

Figure 5: Image similarity at a non-mud pumping location

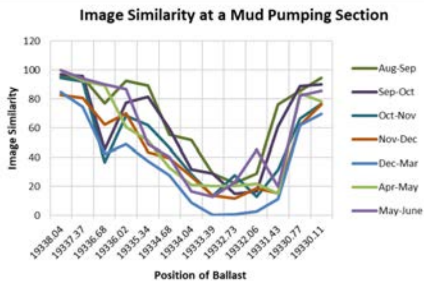

Figure 6: Variation of Image similarity with respect to position and time

28 places of mud pumping were observed in the 12 km stretch. Table 1 summarizes the result obtained by applying only image similarity quantification, only track irregularity check, and a combination of both. Recall shows the ratio of the locations of mud pumping identified using a methodology to the total actual locations of mud pumping. Precision denotes the locations to the number of correctly identified mud pumping locations to the total number of locations identified as mud pumping using a methodology. At few of the joint locations, the magnitude of track irregularity was higher than the threshold, but the image similarity values did not satisfy the criteria to detect mud pumping. By utilizing solely the track irregularity analysis, 86% of the total mud pumping locations were captured. Using only the image similarity analysis, all 28 locations of mud pumping was captured while 52 locations were wrongly assigned to be mud pumping. Locations with high growth of vegetation have low image similarity percentages and cannot be distinguished by the exclusive use of the image similarity values. By combining the image similarity and the track irregularity, the false detection case of mud pumping reduced to 1, while 86% of the mud pumping locations were captured. Thus, the combination of railtrack irregularity and image similarity gives a robust solution for the detection of mud pumping.

	Image Similarity	**Track Irregularity**	**Combination**
Recall	100%(28/28)	86%(24/28)	86%(24/28)
Precision	35% (28/80)	73%(24/33)	96%(24/25)

Table 1: Recall and Precision results with different methodologies: Image Similarity, Track Irregularity and Combination of both

ACKNOWLEDGEMENT:
The authors gratefully acknowledge the invaluable advice of Japan Railway Track Consultants Co., Ltd.

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