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VISION BASED OBSTACLE DETECTION ON RAILWAY TRACK

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Abstract

Novel technology to recognize the human, animals and rocks in rail tracks are essential to develop a railway safety monitoring system. Most of the railway transportation accidents happening at two places, first at the level crossing because of human and animals, second at the mountain side rail track because of the landslide. In this paper, an early warning system is proposed for prevention of these accidents. Early warning system developed using vision based, artificial intelligence and sensors. In this paper, we proposed two methodologies i)A single thermal camera and ADA boost algorithm has been used to detect the obstacle in level crossing and calculating distance between detected obstacle and Train. ii) Artificial intelligence camera setup and image processing to find the landslides over the rail track.

Keywords: Image processing, level crossing, obstacle detection, landslides.

1.INTRODUCTION

In the modern world, the role of railway network is an essential for the people around the world. The railway system consists of infrastructure, development and maintenance. The infrastructure of the railway network is the planning and construction of the rail tracks and establishing their contacts in railway junction. The development of the railway network is used to extent the tracks to the rural and interior areas of the village. The presence of obstacles in the rail tracks threatens the safety of people transportation. The warnings should be given to the relevant units after it is determined whether the obstacles in this rail track cause to an accident or not. It is aimed to prevent the accidents that may be experienced by using the image processing techniques in order to detect by how far the obstacle is located. There are studies in the literature related to the topic.

Silar and Dobrovolny [1] suggested algorithm for obstacle detection and objects tracking in a rail track. The object tracking was based on template matching and the sum of absolute differences. The object tracking was enforced for better reliability of recommended system. The results of method were verified in real traffic scenarios consisted of two railway crossings in the Czech Republic. Maria Molodova et al. [2] proposed a fully automated method for the detection and segmentation of squats in rail system. The authors constructed an efficient method for the railway system by incorporating the automation technique in it. Ze Liu et al. [3] applied the basic principles of Electromagnetic Tomography on rail track image to detect the crack in their running path. The linear backprojection algorithm was constructed to classify the given test source rail track image into either normal or cracked. Based on this classification of rail track, Tikhonov regularization algorithm was applied to validate the experimental results. Yong Shi et al. [4] developed an efficient rail crack detection system using random forest classification technique. The authors extracted integral channel features from real time rail track image and these extracted features were used to detect the crack or defect in rail track images. The topological error of the proposed method was analyzed using the crack detection method.

Amaral et al. [5] presented a system for obstacle detection in railway level crossings from 3D point clouds gained with curved 2D laser scanners. This recommended system was able to gain highly dense and correct point clouds, allowing the detection of small obstacles, like rocks laying near the rail. Throughout an offline training phase, this system learned a background model of the level crossing from a set of point clouds. Then the obstacle was compared online with the background model and identified as the occupied area. To diminish the requirement for manual on-site calibration, this system automatically forecasted the pose of the level crossing and railway according to the laser scanner.

[6-9]To manage the geological risk that involves main infrastructures, different strategies can be adopted: the first one (focused on hazard) consists in monitoring precursors of rock failures by micro- or nanoseismometer recording systems as well as by acoustical emission recording;[10-14] the second one (focused on vulnerability) consists in observing the exposed infrastructure by optical devices (among which cameras, laser scanner, and/or interferometer) suitable for detecting fast changes due to objects/obstacles that impact the infrastructure .

2. Obstacle detection at level crossing.

It is determined a vision based whether or not there is an obstacle at the level crossing that is detected by using image processing techniques as in fig 1.

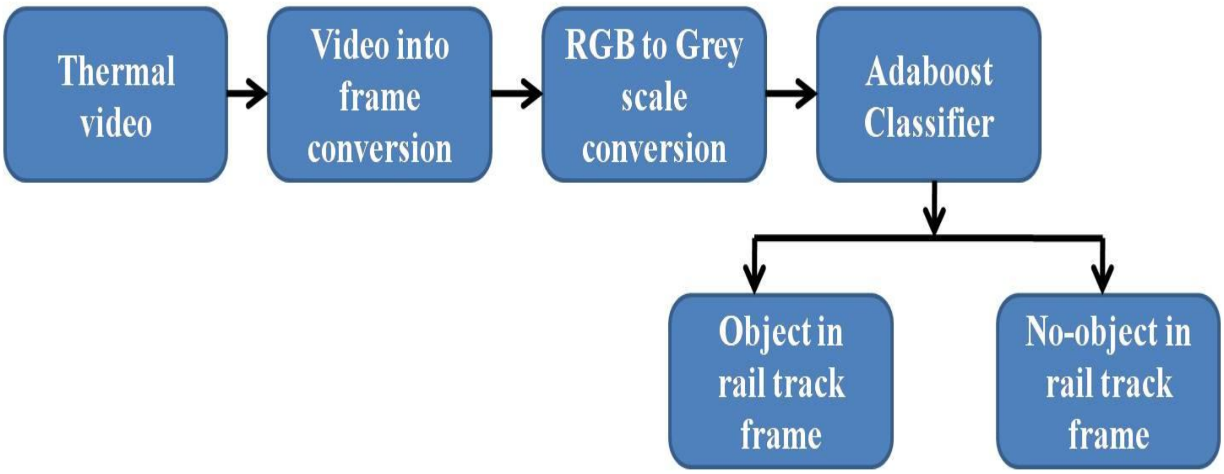


Figure 1 Proposed object detection in rail track system

Then the calculation of the distance between the obstacle and the camera detected has been done. The distance calculation uses the number of pixels covered by the object in the image and the camera distance information from the reference image. The block diagram of the proposed work is shown in Fig. 2.

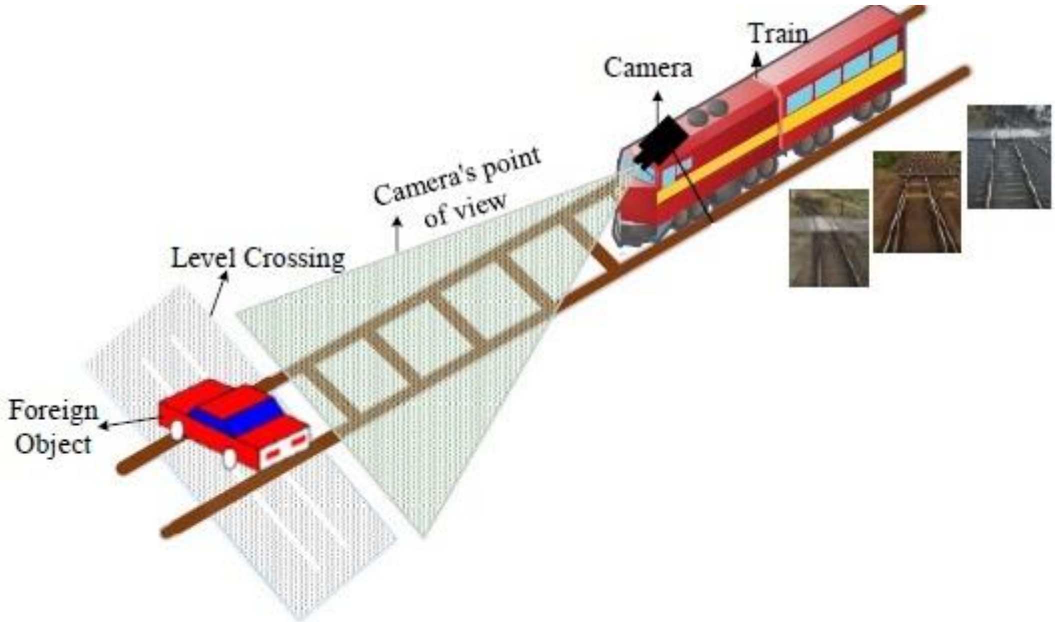


Figure 2 Block Diagram

In the first step of this detection method, the images of the railway have been taken from the camera. Image enhancement techniques have been applied to taken images. Image sharpening and contrast enhancement have been performed in order to advance the images. The remaining steps are list out in the following algorithm.

Algorithm: Object detection in rail track sequences

Input: Thermal rail track video;

Output: Moving object in track frame;

Step 1: Read thermal rail track video in AVI format.

Step 2: Convert the video sequences into number of frames.

Step 3: Convert each RGB frame into grey scale frame format using the following equation as,

- RedConstant * p1.redValue + GreenConstant * p1.greenValue + BlueConstant * p1.blueValue = p1.grayValue;
- RedConstant * p2.redValue + GreenConstant * p2.greenValue + BlueConstant * p2.blueValue = p2.grayValue;

- RedConstant * p3.redValue + GreenConstant * p3.greenValue + BlueConstant * p3.blueValue = p3.grayValue.

Step 4: The grey scale frames are passed to the Adaboost classifier to classify each frame into either the object crosing frame or non-object crosing frame.

Adaboost Classification

In this paper, Adaboost classification algorithm is used to classify each frame in thermal video into either object crosing frame or non-object crosing frame. The Adaboost classification algorithm is explained in the following steps as,

Step 1: From the set of grey scale frames, find test sequences using the following equation as,

T= (x1,y1)……(xn,yn);

Step 2: Determine the internal weight of each frame using the following equation as,

W(i)=$\frac{1}{k}$;

Where, k=1,2,…..N;

And N is the total number of frames in video sequences.

Step 3: Compute standard deviation σ_i of each frame in video sequence.

Step 4: Find the error rate of the frame sequence using the following equation as,

$\Psi_i=\sum_{i=1}^{N} w(i) * frame(i)$

Step 5: Determine the frame which has high value of Ψ, is identified as moving object in track.

3. Obstacle detection during landslides

For managing geological risk due to landslides, where important infrastructures like railways, are exposed elements. In this regard, an Artificial intelligence Camera setup for real-time monitoring has been integrated with image processing monitoring system devoted to rock fall detection. Sample railway track was used as a target for fallen blocks, Main goals of the test is to detecting rock blocks that reach the railway track. At this aim, several experiments were carried out by throwing rock blocks over the railway track. During these experiments, the Artificial intelligence camera setup detected the blocks and automatically transmitted an alarm signal.

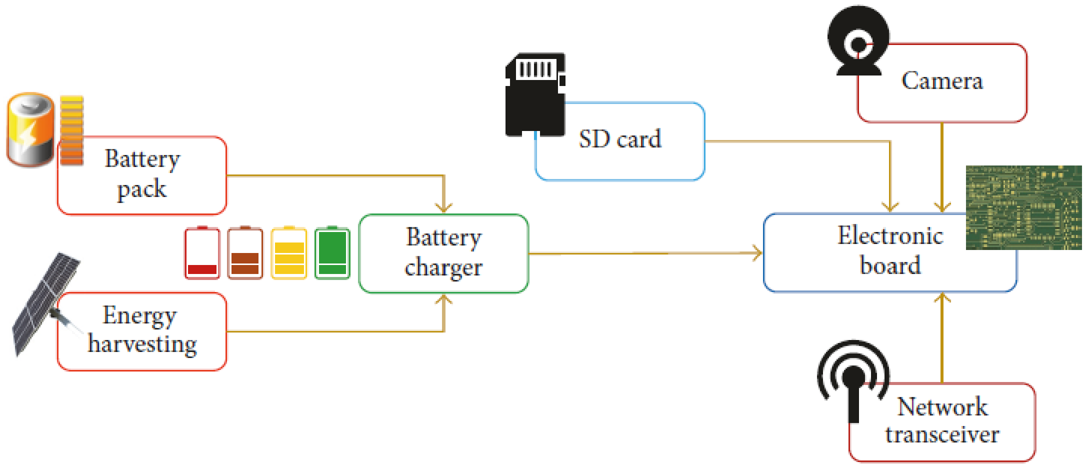


Figure 3 Hardware architecture of camera setup

Figure 4-Hardware components of camera setup

The above setup in figure 4 was fixed in a stand to focus the two region of interest as in fig 5
i) a RoI Of alert, including the monitored quarry wall, where rock detachments are expected
ii) a RoI of alarm, including only the railway track-target that the fallen blocks are expected to reach.

Figure 5-Point of view of camera

Three goals of the system are: (i) detecting obstacle in the RoI of alarm which came from a known direction; (ii) controlling the RoI of alert to identify movement of objects which can impact the railway tracktarget (i.e., entering in the RoI of alarm); (iii) monitoring the two RoIs over a long time (i.e., several months) to check the dynamic updating of the background scenario.All the three goals are achieved by the algorihm in which background scenario is constantly updated by merging the old background scenario with new captured images . The f solution uses an average image in which the background scenario is onboard modelled by averaging the captured frames within a time window, though an equal threshold for all the pixels.

4. Results and Discussion

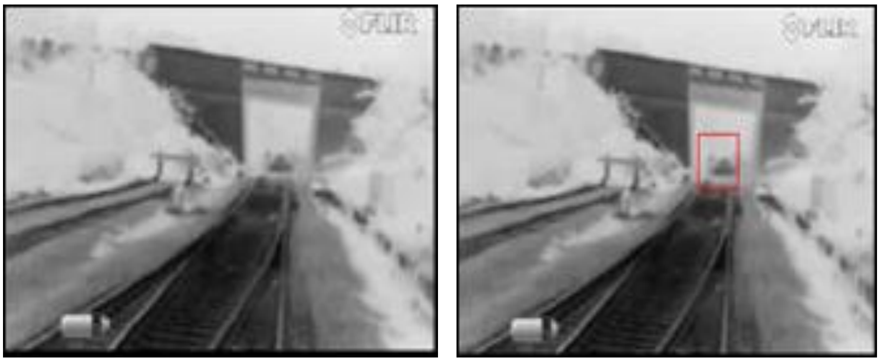
4.1 Obstacle detection at level crossing

The specifications of the thermal video used in this paper are given in Table 1. The width and height of the video frame is 320 pixels and 240 pixels, respectively. The bit rate of the video sequence is 128 Kbps and frame rate is set to 25 frames per second. The video format of the thermal video used in this paper is ADPCM.

Table 1 Specifications of the video source

Parameters	Specifications
Width of video frames (W)	320 pixels
Height of video frames (H)	240 pixels

Bit rate	128 Kbps
Frame rate	25 frames/sec
Video format	ADPCM



(a) **(b)**

Figure 6 (a) Video sequence in thermal video (b) Detected moving object in thermal video

Fig. 6 (a) shows the video frame in thermal video which is the input source of this proposed moving object detection in rail track system. Fig.6 (b) illustrates the detected moving object in rail track sequence.

$$\text{Detection rate} = \frac{Number\ \ of\ \ detected\ \ frames\ \ which\ have\ objects\ \ in\ rail\ \ track}{Total\ \ number\ \ of\ \ frames\ \ which\ have\ objects\ \ in\ rail\ \ track} * 100\%$$

In this paper, the number of detected frames which have objects in rail track is 28 and the total number of frames which have objects in rail track is 30. Hence, the detection rate of the proposed system is 93.33%.

4.2 Obstacle detection during landslides

Fig 7 shows the example of parabolic trajectory of a launched rock block (orange frame). The launched block crosses the RoI of alert (yellow frame) (a); the block falls into the RoI of alarm and rests (red frame c). The change detection analysis quantifies the modified pixels and an alert signal is remotely transmitted to the control station.

Figure 7 Obstacle Detection

5. Conclusion and Future work

The proposed work ensures the safety of passengers in railway transportation, and it helps to managing the geological risks such as landslides. The work can be extended to work with various lighting and various climatic conditions.

References:

[1] Z. Silar and M. Dobrovolny, "Objects Detection and Tracking on the Level Crossing", Computational Collective Intelligence. Springer International Publishing, pp. 245-255, 2015.

[2].M. Maria, L. Zili, N. Alfredo, "Automatic Detection of Squats in Railway Infrastructure", IEEE Transactions on Intelligent Transportation Systems, Vol.15, No.5, pp 1980-1990, 2014.

[3].L. Ze, L. Wen, X. Fangqi, X. Junyan Xiafang, B.Bu, and Y. Zheng, " Electromagnetic Tomography Rail Defect Inspection", IEEE Transactions on Magnetics, Vol.51, No.10, pp. 1-7, 2015.

[4].S. Yong, C. Limeng, Q. Zhiquan, M. Fan and C. Zhensong, " Automatic Road Crack Detection Using Random Structured Forests", IEEE Transactions on Intelligent Transportation Systems, Vol.17, No.12, pp 3434–45, 2016.

[5] V. Amaral, F. Marques, A. Lourenço, J. Barata, and P. Santana, "Laser-Based Obstacle Detection at Railway Level Crossings", Journal of Sensors, Vol: 2016, 2016.

[6] D. Amitrano, J. R. Grasso, and G. Senfaute, "Seismic precursory patterns before a cliff collapse and critical point phenomena," Geophysical Research Letters, vol. 32, no. 8, pp. 1–5, 2005.

[7] D. Amitrano, M. Arattano, M. Chiarle et al., "Microseismic activity analysis for the study of the rupture mechanisms in unstable rock masses," Natural Hazards and Earth System Science, vol. 10, no. 4, pp. 831–841, 2010.

[8] M. Fiorucci, R. Iannucci, S.Martino, and A. Paciello, "Detection of nanoseismic events related to slope instabilities in the quarry district of coreno ausonio (Italy)," Italian Journal of Engineering Geology and Environment, vol. 16, no. 2, pp. 51–63, 2016.

[9] M. Fiorucci, R. Iannucci, L. Lenti et al., "Nanoseismic monitoring of gravity-induced slope instabilities for the risk management of an aqueduct infrastructure in Central Apennines (Italy)," Natural Hazards, vol. 86, pp. 345–362, 2017.

[10] G. Antonello, N. Casagli, P. Farina et al., "Ground-based SAR interferometry for monitoring mass movements," Landslides, vol. 1, no. 1, pp. 21–28, 2004.

[11] X. P. Lai,M. F. Cai, andM.W. Xie, "In situmonitoring andanalysis of rockmass behavior prior to collapse of themain transport roadway in Linglong Gold Mine, China," International Journal of Rock Mechanics and Mining Sciences, vol. 43, no. 4, pp. 640– 646, 2006.

[12] S. Gaffet, Y. Guglielmi, F. Cappa, C. Pambrun, T. Monfret, and D. Amitrano, "Use of the simultaneous seismic, GPS and meteorological monitoring for the characterization of a large unstable mountain slope in the southern French Alps," Geophysical Journal International, vol. 182, no. 3, pp. 1395–1410, 2010.

[13] P. Bigarr´e, E. Klein, Y. Gueniffey, and T. Verdel, "Cloud monitoring: an innovative approach for the prevention of landslide hazards," in Proceedings of the 2nd World Landslide Forum, Abstracts BookWLF2, L16, 475, Rome, Italy, 2011.

[14] S.Martino and P.Mazzanti, "Integrating geomechanical surveys and remote sensing for sea cliff slope stability analysis:The Mt. Pucci case study (Italy)," Natural Hazards and Earth System Sciences, vol. 14, no. 4, pp. 831–848, 2014.

[*15] R. Manikandan , M. Balasubramanian and S. Palanivel "An Efficient Framework to Detect Cracks in Rail Tracks Using Neural Network Classifier" in International Journal of Pure and Applied Mathematics .Volume 116 No. 10 2017, 461-470*

[16] R. Manikandan , M. Balasubramanian and S. Palanivel" Machine Vision Based Missing Fastener Detection In Rail Track Images Using Svm Classifier" in International Journal On Smart Sensing And Intelligent Systems Special Issue, September 2017