A SMART DEVICE FOR MONITORING RAILWAY TRACKS IN REMOTE AREAS

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ABSTRACT

In this paper we present a smart camera prototype capable of performing computer vison tasks directly on-board. The prototype is applied to real time monitoring of railways for detecting fast failures and other hazardous events to train circulation and providing notifications and early warnings to users. Experiments in a test site are reported together with encouraging preliminary results.

Index Terms – Real-Time Imaging, Embedded Systems, Smart Camera, Railway Monitoring.

1. INTRODUCTION

In the last years, particular attention was focused on the monitoring of fast to very fast failures, which include landslides from rocky slopes (e.g. falls, topples and wedge sliding), but also sinkholes and debris flows channeled along high-inclination slopes. The relevance of such events is mainly related to the short time available for taking action in case of exposed infrastructures (highways, railways and so on), since no significant displacements are generally detected before failure. In this regard, the possible strategies to manage the natural risk are: i) monitoring precursors by using micro- or nano-seismometric devices as well as of acoustical emission records [1], [2]; ii) monitoring the site as well as the exposed infrastructures, by using optical devices (e.g. cameras, interferometers, videos) capable of detecting fast morphological changes or abnormal and unexpected objects hazardous for the infrastructure [3], [4], [5], [6] and [7].

The main purposes of monitoring are to investigate or detect the site at different evolutionary stages, corresponding to different distributions of the landslide hazard and to understand and control the parameters for forecasting the short-term evolution of gravitational instabilities. In case of railways, another important point is represented by detection of obstacles along the track that can be dangerous for train circulation. With respect to the previous works cited above, in this paper an approach based on smart cameras is presented for pervasive monitoring of railways. Each smart camera is a completely wireless and self-powered device that observes a portion of railway and its surrounding in order to detect obstacles, accumulation of debris and gravitational instabilities. To this end, smart cameras are equipped with specially-designed computer vision algorithms that are deployed on board the camera to analyze in real time the scene and provide an interpretation. With respect to other solutions, the proposed one is low cost, easy-to-install and scalable. Indeed, a special prototype of smart camera that is possible to produce at low cost is used. Being wireless and self-powered, the camera does not need major works to be wired and installed: it is sufficient to mount it on a pole. Finally, since the camera does not need to transmit images routinely but just few bytes are necessary to describe the output of processing, many smart cameras can be installed to monitor a wide area, with no scalability concerns.

The main contributions of the paper are the following. First, the specially designed smart camera prototype is introduced and described. The device has good features that make it useful for several applications in vision-based monitoring, especially when a self-powered solution must be adopted. Then, computer vision methods realized ad hoc for the smart camera prototype and the application to railway monitoring are introduced. Although being based on simple video analytics, the algorithms are optimized for deployment on an embedded device such as the proposed smart camera. Finally, the efficiency of the computer vision algorithms and the suitability of the smart camera approach are proved through real tests in a sample scenario that has been setup. The overall system was able to detect dangerous obstacles and to detected landslides and gravitational instabilities and showed to be reliable in continuous monitoring of infrastructures.

2. MATERIALS AND METHODS

In this section the smart camera prototype is introduced and detailed and, then, the developed computer vision methods dedicated to railway monitoring are described.

2.1. Smart camera prototype

A prototype of smart camera was designed and developed targeting real time monitoring applications based on vision.

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It consists in a custom embedded computing board equipped with a webcam; the device can deploy on board computer vision algorithms in order analyze the acquired images and transmit the result of processing through suitable network interfaces. In the design of the prototype, an important requirement was the use of low-cost technologies, so that, once engineered, the device can be manufactured at low cost in large quantities. In the design and planning of the architecture, an important consideration was the ease of installation of the device: the protective shield used for the sensor nodes was compact but capable of accommodating all the components of the device.

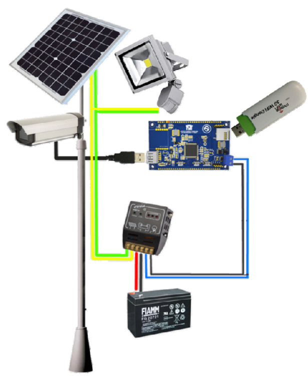

Figure 1. Sensor prototype for railway monitoring

Going into detail, each device has a main board that manages both the vision tasks and the networking tasks. The main board was conceived to have maximum flexibility of use while maximising the performance/consumption ratio. A good compromise was achieved by using a Freescale CPU based on the ARM architecture, with support for MMU-like operating systems GNU/ Linux. This architecture has the advantage of integrating a Power Management Unit (PMU), in addition to numerous peripheral interfaces, thus minimizing the complexity of the board. It is low-power, having an average consumption, measured at the highest speed (454MHz), of less than 500mW. The board has several communication interfaces including an RS232 serial port, SPI, I2C and USB.

For integration of a camera sensor into the vision board, some specific requirements were defined in the design stage: ease of connection to the board and of management through it, and minimum performance under difficult visibility conditions, i.e. night vision. Thus, the minimal constraints were: compliance with USB Video Class devices [8] and possibility to work in low light conditions. More details on the main board can be found in [9] and [10].

The board supports several networking interfaces including Ethernet, Wi-Fi and 3G. For application to railway monitoring, 3G communication has been selected and an USB modem offering speeds up to 7.2Mbits/s has been integrated.

The previously described board and camera were housed into an IP66 shield. Other important components of the device are the led illuminator, the power supply and the energy-harvesting module through photovoltaic panel. The led illuminator guarantees operation of the device also at nighttime and in low illumination conditions, while the battery and the panel make the device completely self-powered. Battery voltage is monitored through one ADC on the main board: this allows choosing optimal energy-savings policies. See Figure 1 for an overview of the general setup of the smart camera.

2.2. Computer vision methods for fast failures detection

The sensor prototype for fast failure detection was designed and implemented in order to efficiently perform computer vision tasks in real time. Other typical examples of computer vision methods used in open environments such as info-mobility studies for events detection are using more demanding algorithms and methodologies (see [11], [14] and [15]), and are often fully connected in terms of energy and network. In other application domain, as Intelligent Transport Systems such a device has already been tested successfully [10], [12], [13], but this condition is not completely suitable for a strict real-time monitoring as the one that is needed in our case study, where also the energy and networking connectivity raise issues. To this end, the adopted approach was to analyze only the regions of interest regarding a pre-alerting area (i.e. typically parts of rocky walls enclosing the railway line), and the real monitoring area along the railroad track.

In particular, three different situations to be monitored were identified from the requirements: a) presence of a substantial obstacle within the railroad track area, and possible identification of the arrival direction; b) long term monitoring of the whole area under surveillance; and c) pre-alerting area monitoring, in order to identify an accumulation of debris, which could be significant and dangerous for subsequent landslides over the railway.

In order to preserve the real time characteristics and to address all possible issues deriving from the requirements, various algorithms have been instantiated. Taking into account the common issues raised by the previously mentioned requirements, a more general algorithm covering issues in a) as well as in c) has been designed, and its flow diagram is shown in Figure 2. The algorithm as it is depicted represents the most peculiar situation, where an obstacle arriving from a monitored region of interest (i.e. pre-alerting area) “rolls” to the tracks area and stops over there, representing a danger to the railway. As particular instances of this, firstly, the lower part of the chart is used as simple obstacle detection along the railroad tracks (requirement a)), based on simple motion detection in a region of the image. Secondly, a long-term instantiation of the upper part of the diagram is used as a detector of debris accumulation in the pre-alert area (requirement c)). Finally, statistical data on the whole algorithms are used to maintain a long term monitoring of the global area under surveillance (requirement b)). The real time and low consumption constraints brought to the design of algorithms based on the general motion detection paradigm, with restrictions on the area under surveillance. In detail, the "Pre-Alert Area Detection" and "Tracks Area Detection" are performed based on frame differencing of the actual frame versus a dynamically updated background, only on the specific regions of interest (RoIs). Instead, the "Tracks Area Motion", which needs to be more dynamic is performed through a background differencing versus the previously acquired frame (yet only on the specific RoI).

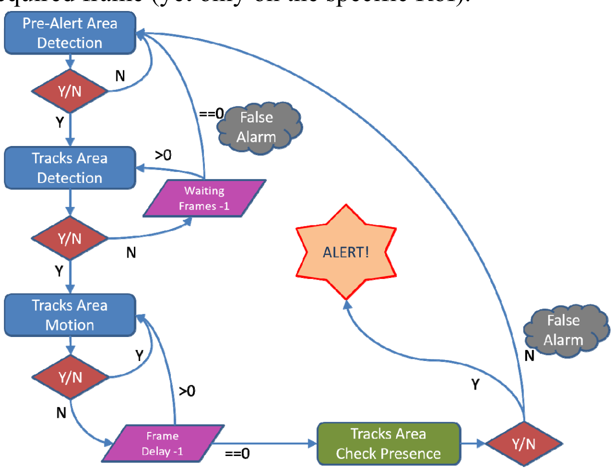

Figure 2. Block diagram of the main computer vision algorithm

In more detail, the "Pre-Alert Area Detection" checks frame at time *t* (called *f(t)*) versus a dynamic background frame *dbf(t)*, which is constantly update at every frame (given that no motion is detected) as a weighted mixture of *dbf(t-1)* and *f(t)*.

$$dbf(t)=(1-w)\cdot dbf(t-1)+w\cdot f(t) \qquad (1)$$

where w is a weight computed in the range [0..1]. The thresholds for the comparison and motion detection are calculated and tested on the base of case study selection.

Once the pre-alert is given (i.e. threshold overcome for at least k consecutive frames), the control goes to the "Tracks Area Detection". The algorithm used here follows the one described for the Pre-Alert Area, with the same dynamic background update policy. The candidate object is expected to reach the rail track area in a number of frames called *Waiting Frames*, which is set specifically for the case study (e.g. it depends on the distance between the 2 areas, from the distance of the camera from the monitored area), in case this time expires without any object being detected on the rail track, then a false alarm is issued. While, in case the object has been detected along the rail tracks, the "Tracks Area Motion" algorithm is applied. This algorithm continuously monitors motion in the track area, by differencing the actual frame versus previous frame (yet within the RoI), and comparing it with a pre-defined threshold. While the object keeps moving inside the track area nothing is changed, but once the motion stops, let us say after m frames, the "Tracks Area Presence Check" is performed. This check consists of a computation of the connected area identified from motion detection performed between actual frame *f(t)* and frame *f(t-m)*. This results is compared with predefined thresholds (representing specific objects, as they appear at the real distance of the camera) to check whether the object is endangering the track area or not, thus yielding an alert or not.

3. EXPERIMENTAL RESULTS

The test-site chosen is a quarry area near Acuto, a small Italian village located about 80 km south of Rome.

The scenario to be monitored consists of a 3 meters long railway track positioned near a rocky wall characterized by a height ranging from 15 meters up to 50 meters.

Our sensor is positioned 6 meters from the railways and it observes an area of size approximately 20x15*m*.

The first part of the experiments has been the calibration of the thresholds used in the algorithms. They depend on the dimension of the rock, the distance of the camera and the possible obstruction in the field of view.

Many rocks of different dimensions were available nearby. 20*cm* and more is the size of the rock that should rise the alarm when it is inside or beside the railway track.

In Figure 3, a rock inside the railway track is used to determine the threshold for the "Tracks Area Presence Check" described in the former paragraph.

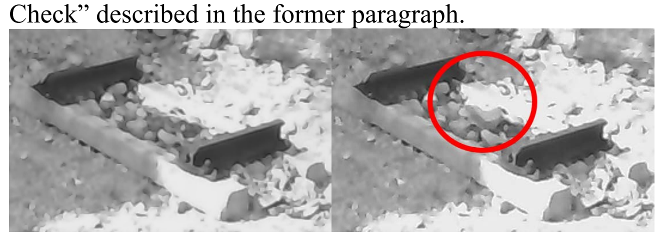

Figure 3 The chosen rock inside the tracks determines the threshold for the "Tracks Area Presence Check"

The second part of the experiment is a simulation of some falling rocks towards the railway track. Different rocks were launched several times with a trajectory that passed through the Pre-Alert Area and ended inside or nearby the railway track (see Figure 4). Table 1 summarizes the results of the simulation, showing a quite good performance on this initial testing. In total over 11 events, all of them were detected from the system, but 7 were issuing alerts, while 4 were not for various reasons: small rocks not endangering the tracks, rocks which have been crumbled by the impact with the tracks or ground, rocks passing over the tracks and stopping outside the tracks area. Therefore, these 4 cases were correctly giving no alert.

Regarding the results at night or with lower visibility, the system is equipped, as mentioned, with LED light and photovoltaic panel to be fully autonomous. Although only few experiments were performed in this scenario, nevertheless the results are promising. In order to guarantee a correct functioning of the detection algorithms, two solutions have been tested: the first one simply correct the thresholds used within the algorithm with respect to the global luminosity of the scene, the second one, performs a histogram adjustment on the acquired image (see Figure 5), and then again thresholds modification is applied. Preliminary results, shown in Figure 6, indicate that simple modification of the thresholds is working but the algorithms are very prone to false alarm generation, while the simple (i.e. not computational demanding) histogram adjustment can be very effective and the dynamic modification of the thresholds is minimal and less prone to yield false alarm, while retaining sensitivity.

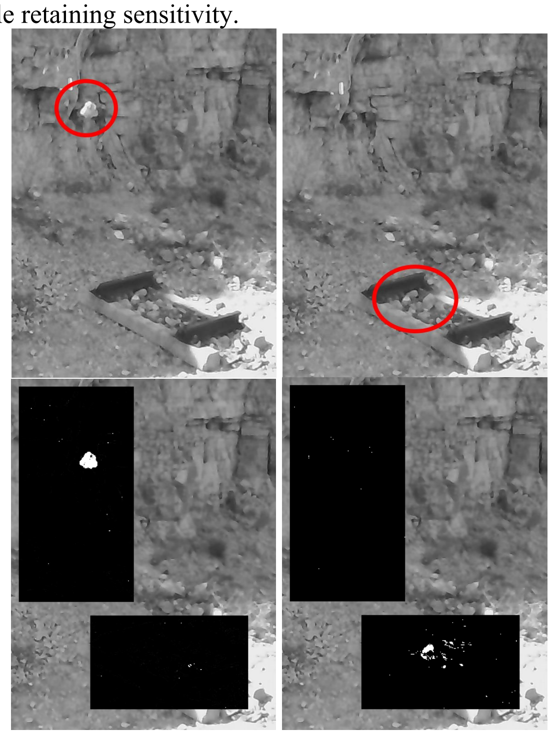

Figure 4 Detection of a falling rock in both Pre-Alert and Track Areas (not masked-upper and masked-lower)

#	TIME	SIZE	RESULT
1	0:25	Medium	**OK (Alert launched)**
2	0:40	Large	**OK**
3	0:51	Small	**NO (small rock below tracks)**
4	1:07	Small/Med	**NO (small rock)**
5	1:22	Small/Med	**OK (rock crumbles into pieces)**
6	1:36	Medium	**OK**
7	1:54	Small	**OK**
8	2:10	Med/Large	**OK**
9	2:30	Medium	**NO (rock crumbles into small pieces)**
10	2:41	Medium	**OK**
11	3:08	Med/Large	**NO (rock falls aside tracks)**

Table 1 Results of the first simulations on the test site.

Figure 5 Night image acquired (left) and after real-time histogram adjustment (right)

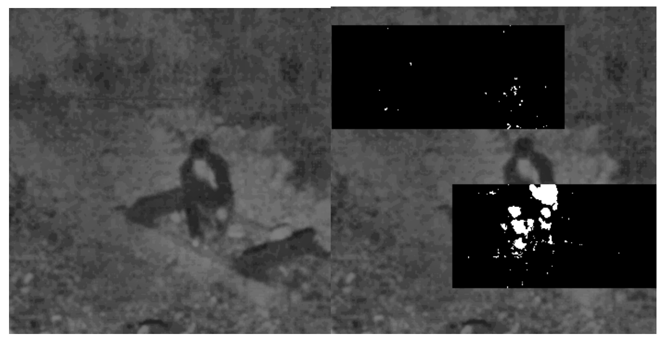

Figure 6 Detected obstacle (actually a person) during night-time on the Track Area (left-not masked, right-masked)

4. CONCLUSION AND FURTHER WORKS

In this paper, a smart camera prototype has been described: it is an embedded device that integrates on board specially designed computer vision algorithms. In the presented application scenario, algorithms are devoted to railway monitoring for assessing the presence of obstacles along the line and instabilities that can lead to landslides and other hazardous events. The camera is able to issue early-warnings in order to avoid conditions that can either impede the circulation or endanger the safety of drivers and passengers. Real tests in a scenario of interest have been carried out simulating rock falls and the presence of obstacles on the line, demonstrating the feasibility of the approach.

In the future, we aim at increasing the experimentation during night-time, and, in case, devising either more sophisticated algorithms or sensors for coping with darkness. In addition, we plan to extend the experimentation to new sites to be monitored, where natural ongoing processes can be detected.

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