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Vision-based change detection for inspection of tunnel liners

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ABSTRACT

Tunnel inspections may demand personnel to access hazardous environments soliciting the need for robotic operations to minimize human intervention. CERN, the European Organisation for Nuclear Research, has a number of tunnel infrastructures, including the tunnel hosting the Large Hadron Collider (LHC). A Train Inspection Monorail (TIM) was installed in the LHC tunnel to reduce personnel intervention. It gathers data from various sensors and captures images which, up till now, were only used for data record purposes. In this paper we present a computer vision system, TInspect, that uses a robust hybrid change detection algorithm to monitor changes on the LHC tunnel linings. The system achieves a high sensitivity of 83.5% and 82.8% precision, and an average accuracy of 81.4%. The proposed system is also configurable through different parameters to adapt to different scenarios, making it useable in other tunnel environments and therefore not exclusive to the LHC tunnel.

1. Introduction

During tunnel inspections, personnel may have to enter hazardous environments. CERN has > 50 km of tunnels, hosting machinery used for different experiments in difficult environments. One of these, is a tunnel hosting the Large Hadron Collider (LHC). To ensure safety, the 27 km long tunnel structure, together with the devices within it, need to be regularly monitored. In order to access the LHC tunnel, personnel require personal protective equipment (PPE) [1]. Access is strict and needs to be coordinated with the CERN Control Center (CCC) beforehand. Furthermore, when personnel enter the tunnel they might be exposed to risks from the presence of radiation, and need to abide by certain rules [2] to keep the dose levels according to the "As Low As Reasonably Achievable" (ALARA) principle adopted at CERN.

These conditions raise the need for an automated inspection system to reduce personnel intervention and help with reducing subjective surveys. Consequently, a remotely operated modular inspection train, the Train Inspection Monorail (TIM) [3] was installed on the overhead track already existing on the LHC tunnel ceiling. Up till now, the train has been used for measuring temperature, radiation levels and to get a remote view of the tunnel. A camera has already been fixed on a robotic arm which extends downwards from one of the wagons. The TIM uses this camera to gather visual data, however, the images captured were only used for data record purposes.

This paper concentrates on the development of TInspect, a vision-based inspection system to be installed on the TIM. The images are shot from small, low-cost camera equipment placed on the TIM. Low-complexity, yet very effective image processing techniques are then applied to these images, in order to detect possible abnormalities on the tunnel linings, which may be indicators of damage and deterioration, such as holes in the wall or wall cracks which have appeared or grown since a previous survey. While automatic tunnel inspections able to detect and classify wall defect and cracks have been recorded in the literature, change monitoring systems are still lacking. Contrastingly, TInspect offers a new means of automatically detecting changes on tunnel wall linings over time. It corrects for position offset between temporal images resulting from image capture position variances due to the moving platform using an alternative approach, that of image mosaicing with binary edge detection as a high level feature for registration. This is followed by a new hybrid change detection algorithm using neighbourhood image differencing, binary image pixel comparison and optical flow. The system achieves both a high sensitivity of 83.5% and 82.8% precision, as well as an average accuracy of 81.4%. This provides a reliable tunnel wall change monitoring framework which is able to detect changes with a resolution of around 10 cm in width or height.

The remainder of this article is structured as follows. Section 2 reviews the state of the art with respect to techniques used, such as change detection and stitching. Section 3 gives an overview of the system. Section 4 discusses the image acquisition part. The pre-processing step is described in Section 5. Section 6 explains image registration as used in the context of the system through a mosaicing algorithm and survey image mapping, with details on each step involved.

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Section 7 investigates the change detection methods implemented while results of the whole system are presented in Section 8. A summary description of the TInspect and a discussion of future work concludes this publication.

2. Background and related work

Tunnel structures made of concrete need to be inspected for cracks, leakages and other issues from time to time. To monitor the structure, automatic inspection systems are advisable to avoid human detection errors, damage or crack misidentification, data management inefficiency, subjective survey reports and personnel presence in harsh environments. Thus various tunnel inspection systems have been proposed in the literature.

A tunnel scanner to capture high-precision panoramic images of the surface of a tunnel lining was developed in [4]. An image mosaicing algorithm was used to splice adjacent images while the gradient of the luminance along line edges was utilized for the detection of cracks. A low cost robotic system was designed in [5] to capture images, process them and then produce maps of tunnel linings for manual detailed inspection afterwards. Crack detection and measurement were achieved in [6] using a mobile robot system consisting of optical, mechanical and data storage devices. Edge detection and neighbour region linking were used for crack detection. An automatic crack detection and classification method for subway tunnel safety monitoring was proposed in [7]. The system developed in [8], uses the Otsu method for leakage recognition and an algorithm based on the features of the local image grid is used to recognize cracks. A general survey on existing robotic tunnel inspection systems can be found in [9].

Detection of cracks using image processing has been explored by many researchers, however literature on comprehensive frameworks to monitor the health of tunnel linings over time using image processing is still lacking. Such a framework should include a complete solution involving two main modules: Image Acquisition and Change Detection. The following sub-sections discuss previous work in the field of each of these modules separately.

2.1. Image data acquisition

Inspection systems need to be ideally unmanned such as in Ref6. The latter system uses a line-scanning camera for crack detection. The system proposed in Ref4, uses combined arrays of line-scanning camera arrays and powerful lighting. Charge-couple device (CCD) line-scan cameras were used in systems [10,11]. While line-scanning cameras acquire data quickly, due to their limited field of view, image distortion can be quite severe and hence the robot motion relative to the target must be carefully controlled. A fisheye camera together with structured light were used for inspection and to determine the robot's location via visual odometry in [12].

The potential of using a simple DSLR (Digital Single Lens Reflex) for image mosaicing is shown in [13]. This technique is mostly manual, requiring known reference points or laser markers and a precise geometry is assumed. A similar system was presented in [14] using a rig of DSLR cameras, however the capture process is manual. The system in Ref5 also uses multiple DSLR cameras in combination with a polarised LED array for lighting. Another project is that of Tunnelings [15]. The tunnel inspection system, developed by Euroconsult and Pavemetrics, consists of cameras and laser sensors, scanning tunnel wall linings at speeds of up to 30 km/h. Such robotic systems can complete the inspection process with objective results and high efficiency.

2.2. Change detection

The majority of currently existing tunnel inspection systems detect cracks and deformities as well as the presence of water along the tunnel linings. However, a rather more useful and informative survey should include regular tunnel inspection to monitor the health of tunnel linings over time. The ability to detect changes that quantify temporal effects using multi-temporal imagery provides a fundamental image analysis tool in diverse applications, thus a considerable amount of research has been done in this field.

For a reliable comparison, the images must be taken from exactly the same point. This is quite a difficult task when the cameras are mounted on a moveable platform. In order to counteract this, images need to be registered first, such that they are spatially aligned. Once this is done, image comparison can be done through simple image differencing, ratioing or various other algorithms.

2.3. Image stitching and mosaicing

In our scenario, images will be continuously captured while the TIM is moving and therefore the exact capture position is almost impossible to match the previous survey. For this reason, a position offset correction method had to be implemented to have a reliable comparison for change monitoring. The use of image mosaicing is proposed for this offset correction, and therefore a brief analysis of the state of the art in image stitching and mosaicing is provided below.

Image stitching algorithms take a multiple number of images as input and combine them to form a larger single image. Applications, include multiple image super-resolution, video stitching, aerial land surveys and medical imaging. Image stitching algorithms are commonly bundled with most digital cameras, smart-phones and tablets to create wide-angle panoramas. Recent surveys of existing image stitching algorithms can be found in [16–18].

A mosaic is generated by stitching multiple rows of photos that were taken without rotating the camera around a single point as in panoramas, but by keeping the camera perpendicular to the subject. Image mosaicing techniques have been reviewed in various publications including [19,20].

Image mosaicing applications share a common pipeline consisting of two stages: Image Registration and Image Compositing. Registration is the process of spatially aligning two or more images of the same scene but taken from different viewpoints, using multiple sensors or even at different dates (due to difference in lighting or other physical conditions). Detailed surveys of image registration techniques can be found in [21–23]. Also, a study of image registration in the context of image stitching can be found in [24].

After aligning the images, the remaining task is to stitch these images to form a single image. Seams along the overlapping area should be as imperceptible as possible and exposure differences between the images to be stitched should be adjusted for to avoid false positives. One method is gain compensation as used in [25]. A number of effects such as, vignetting, registration errors and parallax effects may cause some image edges to be still visible even after such a compensation. Consequently, a blending strategy should be adopted such that the value of each pixel in the overlapping area of the input images are combined using a specific function to produce the value of the pixel in the output image. In this way, the content presents a smooth transition between the images in the final mosaic. Rankov et al. [26] use alpha blending, where proportions of the corresponding image values are taken depending on the distance of the pixel from the image edge. Brown and Lowe [25] use the multiband blending technique which was originally proposed in [27]. The idea of multiband blending is to blend low frequencies over a large spatial range and high frequencies over a short range using blending weights.

2.4. Image comparison

Vision-based inspection change detection involves identifying the differences between two images of the same scene as observed at different times. Image comparison techniques are applied to the images to be able to detect any changes. Pixel-based methods include Image