HKIE THE HONG KONG INSTITUTION OF ENGINEERS 香港工程師學會

Smart watchdog: intelligent virtual checker based on human factors

Rica Ng Chak Lam, Wai Pan Tam, Ching Yin Lau, Jessica Chan, Wing Fung Ko and Arthur Chan
Hong Kong Transport Services Business Unit, MTR Corporation Limited, Hong Kong, People's Republic of China

ABSTRACT

Many operations in the railway rely on manual operations, which means that there are human factors involved. Meanwhile, safety is always the first priority on the railways and is the cornerstone of MTR's success, particularly during these various manual operations. Although there are many safeguards for addressing human factors, these traditional approaches can be complex, may require huge efforts, or may involve additional human resources to perform the checks and balances. Therefore, an innovative methodology called the Smart Watchdog was explored to automatically monitor the manual operations on display screens through the application of artificial intelligence to the videos captured from the display screens. Through a series of artificial intelligence learning, fine-tuning, and testing processes, Smart Watchdog enables accurate and robust detection of the real-time status available on the display screens and generates respective outputs as timely reminders to safeguard potential wrong manual operations. Four representative use cases in MTR are presented in this paper, which shows the significant improvement after the implementation of Smart Watchdog. With this innovative solution, train services can be enhanced and MTR, being one of the leading railway companies, can evolve to be a smart, safe, and efficient railway company.

KEYWORDS Artificial intelligence; computer vision; video analytic; human factor; railway; safety
CONTACT Rica Ng Chak Lam ricang@mtr.com.hk
Received 6 March 2023

1. Introduction

MTR is regarded as one of the world's leading railway operators for safety, reliability, customer service and cost efficiency. The train service operates around 19 hours per day, 7 days per week, covering nine main commuter networks and the Airport Express which were constructed or upgraded during different periods by different system providers (MTR, 2024). Many of the daily operations are conducted manually, which means that these operations depend on human factors. On the other hand, MTR has a brand-new campaign of "Go Smart Go Beyond", and innovation and smart technology are the essential elements for this mission.

The human factor is not a new concept and is a common pain point that exists in many industries. A literature review of human factors in smart factories was conducted in (Silva et al., 2020). Another paper presents a railway infrastructure intelligent monitoring framework tackling human factors and decision-making (Dadashi et al., 2014). Moreover, there have been applications of Artificial Intelligence (AI) in detecting and mitigating human errors in nuclear power plants (Sethu et al., 2022). Many manual operations in railways involve the operation of the computer screens of the system workstations, for example, signalling systems and power systems. From time to time, the need to add safeguards to manual operations arises, for example, due to incidents or near misses that occur during operations. However, there are difficulties or significant cost impacts if these systems are directly modified to incorporate these safeguards. For example, some systems are legacy ones, so software modification may not be practical due to a lack of support or information (e.g., source codes) from the Original Equipment Manufacturer (OEM), or the system specification or the operating platform cannot support the new changes. Another example is that some systems are safety-critical systems, such as signalling systems. Any software modification requires a comprehensive system assurance process, and international standards such as EN50128 shall be followed for software modification of these systems with safety integrity levels. These examples show the complexity and efforts required to incorporate the new safeguards. Another conventional approach to dealing with human factors is the introduction of independent checkers. However, this methodology requires additional human resources and makes the manpower arrangement less flexible.

There are various applications of AI in relation to railways. A paper presents the use of cameras and AI for obstacle detection along railways (Ristić-Durrant et al., 2020). From a holistic perspective, AI can also be applied in maintenance, planning and passenger mobility (Tang et al., 2022). A specific example of AI prediction of equipment failure was applied based on the data collected for the switch points (Arslan and Tiryaki, 2020). In this paper, we explore an AI solution that can be easily added to the existing systems for automatic real-time continuous monitoring of display screens, which is Smart Watchdog. This type of AI design and application is new and novel in the railway industry. This Smart Watchdog solution augments human tasks for monitoring manual operations on display screens and eliminates the need to use an in-person

approach or direct software modification of the existing system. With the popularity of gaming and live streaming on social platforms, there are various types of video capture devices in the market that suit the purpose. These products are adopted in our innovative applications, which facilitate the development of Smart Watchdog for railway systems.

The rest of this paper is organised as follows. In Section 2, we present an overview of the system architecture together with the hardware design and configuration. Section 3 describes the generic design considerations of the Video Analytic Module. In Section 4, we present the specific design considerations of the Video Analytic Module illustrated by three use cases in MTR. Finally, Section 5 provides a summary of the work and discusses the potential future possibilities.

2. System architecture and hardware configuration

In this section, the system architecture and hardware configuration of the Smart Watchdog solution are presented. The system comprises three parts, namely Original Set-up, Smart Watchdog Gadget, and User Interface.

2.1. Original setup

The original setup comprises a computer workstation and computer display screens. The computer workstation and computer display screens are interconnected using video cables. Examples of video connection types are Video Graphics Array (VGA), High-Definition Multimedia Interface (HDMI), DisplayPort (DP), and Digital Visual Interface (DVI). Depending on each system, the resolutions can be 1920×1200, 1920×1080, 1280×1024, etc. Figure 1 illustrates a typical original setup.

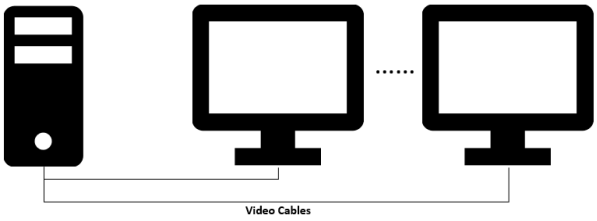


Figure 1. Typical original setup.

2.2. Smart Watchdog gadget

The Smart Watchdog Gadget consists of two major modules, namely the Video Capture Module and the Video Analytic Module. The Video Capture Module accepts video feed split from the workstation (i.e., mirroring the display on the target screen). Most Video Capture Module products in the market support video input as HDMI. As such, video type conversion will be required such that the video output type from the computer workstation can be converted to HDMI. The captured video can then be passed to the Video Analytic Module for processing. For example, Video4Linux (V4L2) over a Universal Serial Bus (USB) connection can be used for the Video Analytic Module to capture the video frames on the Linux platform (The Linux Kernel Archives, 2016). Figure 2 illustrates a conceptual connection of the Smart Watchdog Gadget with the Original Setup. Although one Video Analytic Module is associated with one Video Capture Module in Figure 2, there is a possibility that one Video Analytic Module connects with multiple Video Capture Modules, with each Video Capture Module capturing one screen. A major design consideration of multiple Video Capture Modules is related to the throughput between the Video Analytic Module and Video Capture Modules. For example, if the YUY2 colour encoding system (Windows App Development Documentation, 2021), 1920×1080 resolution and 60 frames per second frame rate are used by the Video Capture Modules, the throughput for each Video Capture Module will be as follows:

$$(1920\times1080)\ \text{pixels/frame} \times 16\ \text{bits/pixel} \times 60\ \text{frames/second}. \quad (1)$$

Nowadays, it is common for the Video Analytic Module to be equipped with USB 3.0 that supports 4.8Gbps by each USB root hub. In other words, each USB 3.0 root hub can support two Video Capture Modules. On the other hand, the power supply from the USB hub is also a consideration. However, most Video Capture Modules consume less power and thus we have fewer concerns. In other words, these applications are in general throughput-limited, rather than power-limited.

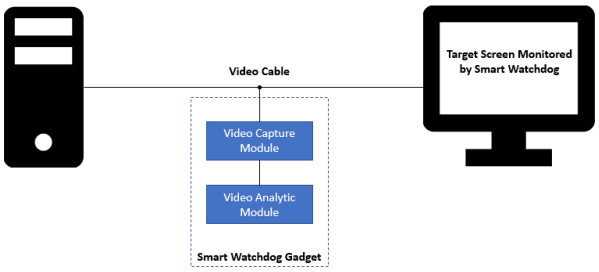


Figure 2. Conceptual connection of the Smart Watchdog gadget with the original setup.

2.3. User interface

After the processing by the Video Analytic Module, the result is available locally. The goal of the whole solution will be to produce the result for the user. Subject to the requirements of individual systems, the User Interface is highly flexible. For example, the result can be directly displayed as a dashboard on a screen, or the result can be made available on a mobile phone connected via wireless technologies, or the result can be uploaded to the cloud

platform. The interface can be either by direct cabling (e.g., video cable), via communication protocols (e.g., WebSocket) or via an Application Programming Interface (API) (e.g., RESTful API). Figure 3 illustrates a conceptual diagram by incorporating the User Interface.

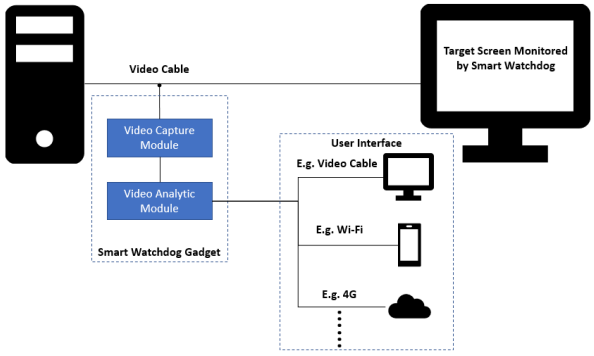


Figure 3. Conceptual diagram of a Smart Watchdog solution.

3. Generic design considerations of the Video Analytic Module

In this section, the key generic design considerations of the Video Analytic Module are introduced for the assurance of the system performance, which is applicable to all applications of Smart Watchdog.

3.1. Detection of loss of video input to the Video Analytic Module

Video input is the main ingredient for Smart Watchdog; thus, it is crucial to ensure the availability of the Smart Watchdog functions and that the video input is normal. There are three major cases of loss of video input. We use OpenCV as an example to illustrate the design principle (OpenCV, 2024).

The first scenario is where the Video Analytic Module software fails to open the connection to the Video Capture Module for the live streaming of video frames. A VideoCapture object can be created, and the method isOpened() can identify whether the capture is initialised successfully by returning a Boolean.

The second scenario is where the Video Analytic Module software fails to receive the frame. The method cap.read() can return a Boolean indicating whether a frame is read correctly.

The third scenario involves the loss of video input in the Video Analytic Module. In this case, a Video Analytic Module feeds a default screen for the no signal case (e.g., black screen or colour bar test screen, depending on individual Video Analytic Module products). Figure 4 shows an example.

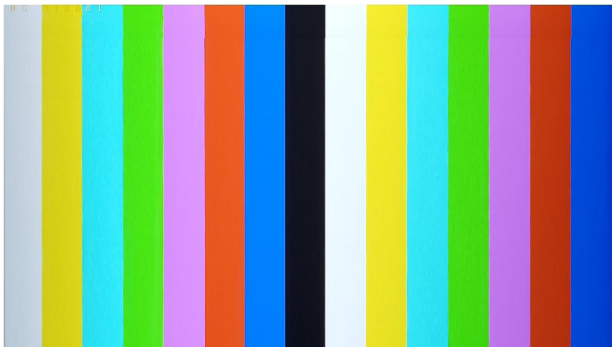


Figure 4. Example of the default screen for no signal.

Mathematically, we denote a frame by I, which is a three-dimensional matrix representing the RGB colour system, and is defined as follows:

$$I: \{0,1,2\} \times \{0,1,\ldots,N_h-1\} \times \{0,1,\ldots,N_v-1\} \rightarrow \{0,1,\ldots,2^N-1\}, \quad (2)$$

where the resolution of a frame is $N_h \times N_v$ and each pixel has N bits. Similarly, we denote the frame for the default screen by Idefault. We can compare the frame with the default screen by calculating the Mean Square Error (MSE) between the frame and default screen as follows (Sammut and Webb, 2011):

$$MSE = \frac{1}{3N_hN_v}\sum_{i=0}^{2}\sum_{j=0}^{N_h-1}\sum_{k=0}^{N_v-1}\left(I(i,j,k)-I_{default}(i,j,k)\right)^2, \quad (3)$$

If the calculated MSE is below a pre-defined threshold, it will be considered as a loss of video input at the Video Analytic Module.

3.2. Detection of frozen video input to the Video Analytic Module

Ensuring that the video input is up to date is important. In general, there is a real-time clock or other dynamic areas on the computer screen, which change frequently to enable users to know that the system is alive. We can crop the part of the image containing a real-time clock or dynamic areas for every frame (Figure 5 shows an example), assuming the cropped size is $N_{crop\_h} \times N_{crop\_v}$, and denoting the two frames as I_0 and I_1 as follows:

$$I_0, I_1: \{0,1,2\} \times \{0,1,\ldots,N_{crop\_h}-1\} \times \{0,1,\ldots,N_{crop\_v}-1\} \rightarrow \{0,1,\ldots,2^N-1\}. \quad (4)$$

Similarly, we calculate the MSE between I_0 and I_1 as follows by using Equation (3):

$$MSE = \frac{1}{3N_{crop\_h}N_{crop\_v}}\sum_{i=0}^{2}\sum_{j=0}^{N_{crop\_h}-1}\sum_{k=0}^{N_{crop\_v}-1}\left(I_1(i,j,k)-I_0(i,j,k)\right)^2. \quad (5)$$

If the MSE is below a pre-defined threshold for a pre-defined number of consecutive frames, it will be considered as frozen video input at the Video Analytic Module.

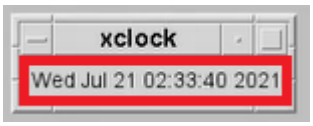
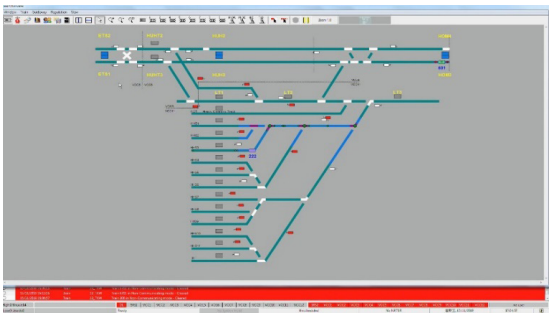


Figure 5. Example of real-time clock cropped.

3.3. Detection of a changed screen layout

Smart Watchdog monitors pre-defined areas of a computer screen. Ensuring the screen layout is the expected one to be detected is crucial to ensure the performance and accuracy of Smart Watchdog. In other words, any change in screen layout can affect the detection performance. The methodology is similar to handling the third scenario of Section 3.1., but the compared image is the expected layout instead of the default screen. If the MSE calculated exceeds the pre-defined threshold, it will be considered as a change in screen layout. Figure 6(a) shows an example of the expected layout, while Figure 6(b) shows an example of a changed screen layout.

(a)



(b)

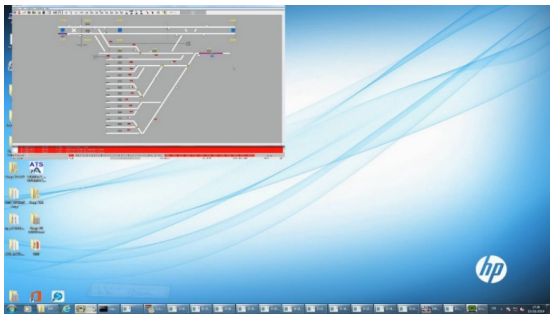


Figure 6. (a) Example of expected layout; and (b) example of changed screen layout (resised on desktop).

Another possible approach is to select checkpoints on the layout. A MSE calculation is adopted similarly. If the MSE calculated for these checkpoints exceeds the pre-defined threshold, it will be considered as a change in screen layout.

4. Specific design considerations of the Video Analytic Module

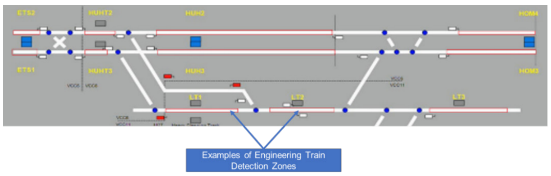
In this section, four use cases are introduced as examples, and the key design considerations of the Video Analytic Module specific for these use cases are explained.

4.1. Smart Watchdog for route setting monitoring in the Hung Hom Siding

In the Hung Hom Siding, some routes comprise severe track profiles with short transitions which are not suitable for engineering trains due to the potential derailment risk. To prevent engineering trains from running along these routes, real real-time monitoring and an alert system applying Smart Watchdog were developed to timely provide warnings to operators when there is a wrong route setting for engineering trains.

To visualise Smart Watchdog, there are 11 engineering train detection zones and 27 point-lock detection zones defined in the Hung Hom Siding area. Figure 7(a) shows the engineering train detection zones, while Figure 7(b) shows the point-lock detection zones. The Video Capture Module directly accepts 1920×1080 video output from the Automatic Train Supervision (ATS) workstation and displays the ATS workstation on the ATS monitor display through the 1920×1080 loop out port. Converters are used for the conversion between DP and HDMI. Through analysing the captured videos, Smart Watchdog monitors the existence of an engineering train in the detection zones and the status of the point-locks, deduces whether the engineering train will be routed onto the forbidden tracks, and generates warnings to operators accordingly in the form of a dashboard on a dedicated monitor display connected to the Video Analytic Module.

(a)



(b)

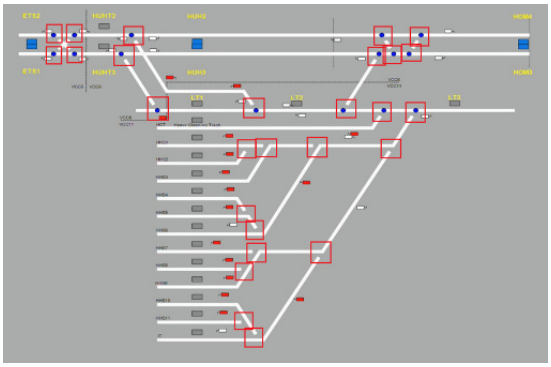


Figure 7. (a) Engineering train detection zones; and (b) point-lock detection zones.

With consideration of the variety of train icons and point-lock notations, a Convolutional Neural Network (CNN) was adopted for the deep learning model of Smart Watchdog which does not require hand-crafted feature extraction (Khan, 2018). For each engineering train detection zone, Smart Watchdog detects the existence of an engineering train and returns the result as "Exist" or "Not Exist". For each point-lock detection zone, Smart Watchdog detects the point-lock status and returns the result as "Normal", "Reverse" or "Undefined".

4.2. Smart Watchdog for power switching communication enhancement in the Operations Control Centre

Every night after traffic hours, also known as the Non-Traffic Hours (NTH) period, the Operations Control Centre carries out the power switching process to switch off the overhead line power for Urban Lines (URL) and Airport Express Line, Tung Chung Line and Disneyland Resort Line (AT&D). This is an essential process so that the working teams can safely commence their various engineering activities, such as maintenance, along the trackside. Moreover, this is also critical for resuming the train services on time on the next day. The process relies on the communication between the Traffic Controller (TC), who is responsible for the traffic management of a railway line and request for power switching, and the Power System Controller (PSC), who is responsible for the execution of power switching operations. Any misoperation may cause safety concerns, late commencement of NTH activities (affecting maintenance efficiency), or late resumption of next-day train services (affecting train service delivery).

Each switch operation is described by a Sequence of Control (SOC), which corresponds to whether the operation is switching on or switching off the power, the planned time of conducting this operation, and the traction power zone involved. To visualise Smart Watchdog in this scenario, TC and PSC are each provided with a tablet, which is interconnected with the Video Analytic Modules via the local Wi-Fi network. TC submits the SOC requests through his/her provided tablet during the conversation with PSC, and PSC can acknowledge the requests through his/her provided tablet. When PSC attempts to execute the switching operations on the Power Remote Control (PRC) workstation (for URL) or Main Control System (MCS) workstation (for AT&D), Smart Watchdog verifies whether the SOC to be executed belongs to those requested by TC and acknowledged by PSC. For correct cases, Smart Watchdog will generate a correct result on PSC's tablet. For incorrect cases, a warning will be generated on PSC's tablet by Smart Watchdog. Figure 8 summarises the operation flows for existing and newly added procedures.

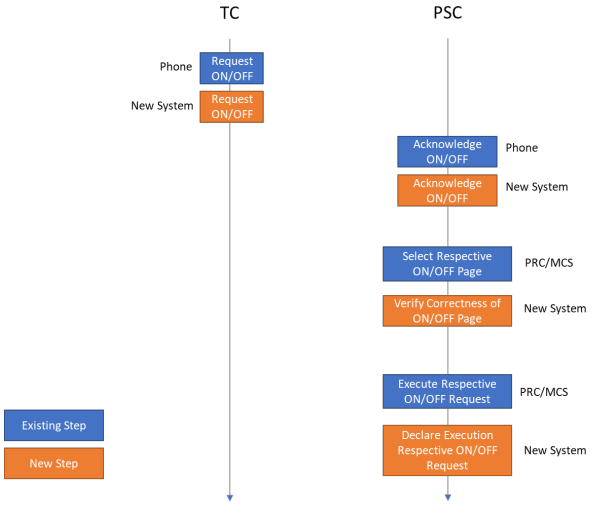
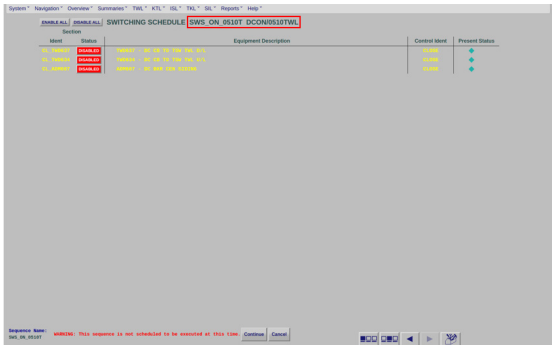


Figure 8. Operational flow of power switching.

With consideration of the distance between PRC or MCS workstations and the Video Capture Modules and Video Analytic Modules, splitters are adopted and installed close to the PRC or MCS workstations to simplify the cable diversion work during cut-off. Another reason for using separate splitters is due to the resolution of the PRC or MCS workstations, which are not 1920×1080, while the loop-outports of the majority of products in the market are 1920×1080. The PRC workstations have a resolution of 1920×1200, while the MCS workstations have a resolution of 1280×1024. To ensure that the existing resolutions displayed to users are not altered, separate splitters are thus used. Furthermore, the DP connection in existing PRC workstations and VGA connection in existing MCS workstations are converted to HDMI for the Video Capture Modules. The SOC detection zone is defined on the screens of the PRC or MCS workstation. Examples are shown in Figure 9(a) and (b). To enhance the detection accuracy and

robustness, the SOC detection zone is cropped, converted to a greyscale image and passed through a noise reduction filter (Lim, 1990). Next, Optical Character Recognition (OCR) is applied to the SOC detection zone (Apostolico, 1997). After that, the OCR result is matched with the SOC having the closest Levenshtein distance (Apostolico, 1997).

(a)



(b)

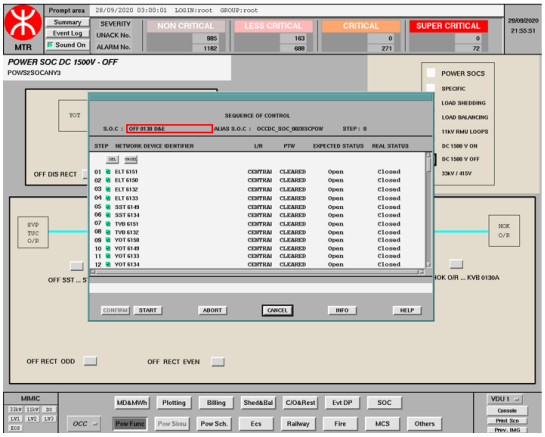


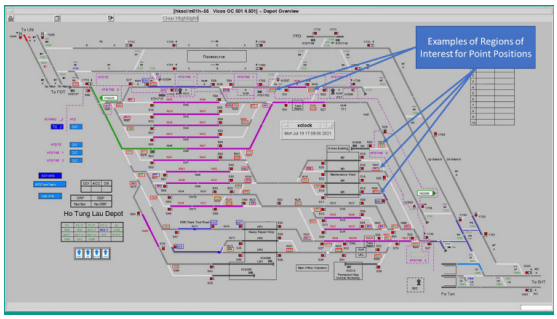
Figure 9. (a) Example of the SOC Detection Zone for URL; and (b) example of the SOC Detection Zone for AT&D.

4.3. Smart Watchdog for depot train movement monitoring

In depots, the train movements are conducted in manual mode. The train operators must observe the signals and point status during train movements. The signals and point status are set according to the route reserved for the train. There are safety concerns or impacts on dispatching trains for service if the train movements are not carried out according to the signals and point status.

We applied Smart Watchdog in Ho Tung Lau Depot serving the East Rail Line. All information related to point positions and signal status is already available on the ATS workstation. We converted the original mini-DP video signal of resolution 1920×1080 to HDMI for our Video Capture Module, followed by looping out the signal to the original computer screen. The regions of interest corresponding to the point positions and signal status inside Ho Tung Lau Depot are illustrated in Figure 10(a) and (b), respectively.

(a)



(b)

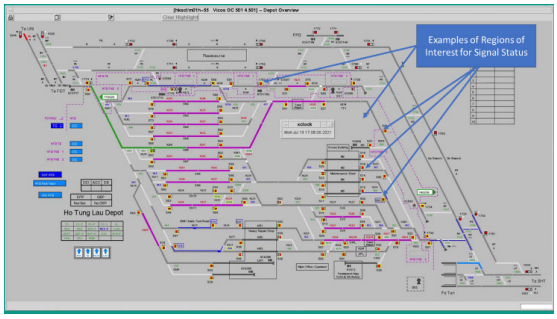


Figure 10. (a) Regions of interest for point positions; and (b) regions of interest for signal status.

In the design of the ATS workstation, the colours reflect the information. For example, the colour of the point name reflects whether it is “Normal”, “Reverse”, “Undefined” or “Fault”. Similarly, the colour of the signal symbol reflects whether it is “Proceed” or “Stop”. To enable accurate and robust detection of the colour of the region of interest, the frame image is converted to a HSV colour system (Albalate, 2011). The advantage of using HSV is that colour information can be obtained by manipulating only one component (i.e., hue), instead of using three components in the RGB colour system, which can largely simplify the computation process. A histogram is applied for presentation of the hue spectrum (Lim, 1990). Only the relevant ranges corresponding to the target colours are extracted to minimise the disturbance due to background colour and shading effects around the edges of the wordings or symbols. Supervised machine learning is applied to categorise the probability distributions in the hue ranges in relation to the given set of possible colours (Albalate, 2011). The point positions and signal status are real-time uploaded to the cloud platform of another interfacing system via a 4G module connected to the Video Analytic Module. The cloud platform provides alerts to train operations via a mobile app with the respective information about the point position and signal status based on the real-time train location during train movements.

4.4. Smart Watchdog for wayside control unit border alerts

On the East Rail Line, there are various wayside control units and borders between areas under the

responsibility of adjacent wayside control units. Some undesired situations are presented by specific types of track occupancy patterns for a specific type of train. Figure 11 illustrates one of these cases via simulation. Our objective is to real-time monitor the ATS workstation and generate alerts when any of these cases are detected. The setting is similar to Section 4.3, but we extended the screen using a spare video output port on the ATS workstation. We converted the original mini-DP video signal of resolution 2560×1440 to HDMI for our Video Capture Module.

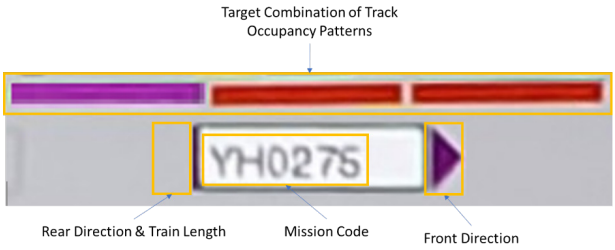


Figure 11. Simulated case for wayside control unit border alerts.

The colour of the track occupancy can be identified by using a similar approach to that discussed in Section 4.3. Template matching methodology was then adopted to match the type of train from the train icon, by applying convolution on the input image while using the template image as a filter (OpenCV, 2024). Moreover, to enhance the accuracy and efficiency of template matching, pre-processing such as converting the colour image to a binary image through applying thresholding was conducted (OpenCV, 2024). The train direction can be determined by identifying which direction the triangular shape is pointing in. The length of the train can be determined by the presence of a flag at the tail of the train icon. In this application, only a nine-car train (i.e., without the flag) was considered. Finally, the mission code of the train, i.e., the characters and numbers in the train icon, provides us the information about whether the train is a passenger train that we should consider.

5. Summary and future work

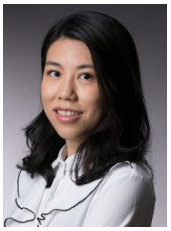
Undoubtedly, manual operation is always one of the key challenges of railways, which can lead to an impact on safety and train services. Safety is the cornerstone of MTR's success, and innovation and smart technology are the core of MTR's latest mission of "Go Smart Go Beyond". Smart Watchdog is a cost-effective and robust AI solution for monitoring these manual operations through computer vision on display screens where humans operate directly, or human operations are reflected. In the four use cases discussed in this paper, thousands of frames were captured from each live system for the training and validation of each AI model in the bench setup. The setup was then deployed to the site for a shadow run to ensure reliability and enable further fine-tuning to uplift the accuracy and performance. Upon completing this series of tests, the systems were launched for operations. Smart Watchdog is proven to be an effective solution to avoid human errors; for example, there has been no wrong power switching operation executed after the deployment of Smart Watchdog.

As a next step, we will explore extending the aforementioned use cases to other railway lines of MTR. Furthermore, there are potential opportunities to apply Smart Watchdog to other systems or even other industries, locally in Hong Kong or internationally.

Notes on contributors

Miss Rica Ng is a Design Engineer in MTR. She holds a BEng in Information Engineering from the City University of Hong Kong, with a focus on networking and communications, algorithms and optimisation, software technologies, and signal processing. In MTR, Rica mainly works on innovative projects, aiming to impact the industry and world by leveraging various advanced technologies. She was also an award-winner in a local engineering competition during her first working year.

Ir Dr Wai Pan Tam is a professional railway design manager in MTR and an active participant in innovation projects, who has received recognitions in various competitions on innovations both locally and internationally. He received his BEng and Ph.D. degrees in Information Engineering from The Chinese University of Hong Kong and specialised in advanced wireless technologies and communication theory. He is also experienced in the applications of artificial intelligence, computer vision, video analytics, and the Internet of Things in railways. He has been a training tutor of Scheme "A" Graduate Training of HKIE since 2017 and is now an engineering supervisor of the scheme.



Ms Ching Yin Lau is currently a Senior Design Engineer in MTR and participates in various technology innovation projects. She received her BEng degree in Computer Engineering at HKUST, and MSc in EEE degree in HKU. She is experienced in design for communication systems and system integration.

Miss Jessica Chan is a railway engineer in MTR responsible for technical design. She received her BEng in Electronic and Computer Engineering from The Hong Kong University of Science and Technology and MSc in Electrical and Electronic Engineering from The University of Hong Kong. She has been actively engaged in innovation projects specialising in Video Analytic and robotics and the development of various applications for the railway industry.

Mr Wing Fung Ko is a railway engineer in MTR and has a wide range of knowledge about new technology applications. He received his BEng degree in Electronic Engineering and an MSc degree in Big Data Technology from The Hong Kong University of Science and Technology. As a control engineer in MTR, he is responsible for the design work of the major station control systems including power control and environmental control as well as the software governance for safety assurance. He is also familiar with the use of cloud technology to enhance railway system resilience and computer vision to improve railway operations.

Mr Arthur Chan is a Maintenance Engineer in MTR specialising in electrical power distribution, who is passionate about joining innovation projects for enhancing railway operations. He graduated from The University of Hong Kong with a BEng degree in Electrical Engineering. His final year project focused on the study of the Internet of Things in smart buildings with advanced wireless technologies, artificial intelligence, and network architecture.

References

[1] MTR (2024). *MTR*. [online]. Available at: <http://www.mtr.com.hk>. [Accessed on 8 August 2024].

[2] Silva VL, Kovaleski JL, Pagani RN, Corsi A and Gomes MAS (2020). The human factor in the smart industry: A literature review. *Future Studies Research Journal: Trends and Strategies*, 12(1), pp. 87-111.

[3] Dadashi N, Wilson JR, Golightly D and Sharples S (2014). A framework to support human factors of automation in railway intelligent infrastructure. *Ergonomics*, 57(3), pp. 387-402.

[4] Sethu M, Kotla B, Russell D, Madadi M, Titu NA, Coble JB, Boring RL, Blache K, Agarwal V, Yadav V and Khojandi A (2022). Application of Artificial Intelligence in Detection and Mitigation of Human Factor Errors in Nuclear Power Plants: A Review. *Nuclear Technology*, 209(3), pp. 276-294.

[5] Ristić-Durrant D, Haseeb MA, Franke M, Banić M, Simonović M and Stamenković D (2020). *Artificial intelligence for obstacle detection in railways: Project SMART and beyond*. In: Dependable Computing-EDCC 2020 Workshops. Munich: Springer International Publishing. pp. 44-55.

[6] Tang R, De Donato L, Besinović N, Flammini F, Goverde RM, Lin Z, Liu R, Tang T, Vittorini V and Wang Z (2022). A literature review of Artificial Intelligence applications in railway systems. *Transportation Research Part C: Emerging Technologies*, 140, 103679.

[7] Arslan B and Tiryaki H (2020). Prediction of railway switch point failures by artificial intelligence methods. *Turkish Journal of Electrical Engineering and Computer Sciences*, 28(2), pp. 1044-1058.

[8] The Linux Kernel Archives (2016). *Part I - Video for Linux API*. [online]. Available at: <https://www.kernel.org/doc/html/v4.9/media/uapi/v4l/v4l2.html>. [Accessed on 8 August 2024].

[9] Windows App Development Documentation (2021). *Recommended 8-Bit YUV Formats for Video Rendering*. [online]. Available at: <https://docs.microsoft.com/en-us/windows/win32/medfound/recommended-8-bit-yuv-formats-for-video-rendering>. [Accessed on 8 August 2024].

[10] OpenCV (2024). *OpenCV*. [online]. Available at: <https://opencv.org/>. [Accessed on 8 August 2024].

[11] Sammut C and Webb GI (2011). *Encyclopedia of Machine Learning*. Boston: Springer.

[12] Khan R, Rahmani H, Shah SAA and Bennamoun M (2018). A *Guide to Convolutional Neural Networks for Computer Vision*. Morgan & Claypool Publishers.

[13] Lim J (1990). *Two-dimensional signal and image processing (Prentice Hall signal processing series)*. Englewood Cliffs, N.J.: Prentice Hall.

[14] Apostolico A and Galil Z (1997). *Pattern matching algorithms*. New York: Oxford University Press.

[15] Albalate A and Minker W (2011). *Semi-supervised and unsupervised machine learning: Novel strategies (ISTE)*. London: ISTE.