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USING A VIRTUAL TWIN OF A BUILDING TO ENSURE SECURITY IN EDUCATIONAL INSTITUTIONS

Abstract. This research paper delves into the exploration of computer vision technology and digital twins as a means to enhance security measures in educational institutions. The study primarily focuses on the creation of a virtual replica of the first floor of a school and the integration of a person detection algorithm with the existing surveillance cameras. By leveraging the capabilities of the digital twin and real-time monitoring, comprehensive surveillance of the premises becomes feasible, resulting in simplified security operations. The paper sheds light on the significant potential of training neural networks for specific security tasks, such as the identification of weapons or the detection of anomalies in human behavior. These trained neural networks can be seamlessly integrated into the digital twin, thus ensuring public safety within the educational environment. The findings of this study provide substantial evidence for the effectiveness of computer vision technology and digital twins in bolstering security measures. The ability to create a virtual representation of the school's first floor enables comprehensive monitoring and surveillance, aiding in the prevention and prompt response to security incidents. The integration of person detection algorithms further enhances the system's capabilities by automatically identifying and tracking individuals within the premises. Additionally, the deployment of neural networks for specialized security tasks adds an extra layer of protection, enabling the identification of potential threats and the detection of abnormal behavior patterns. By employing computer vision technology and digital twins, educational institutions can establish an advanced security infrastructure that optimizes monitoring, enhances situational awareness, and ensures a safer environment for students, staff, and visitors. The research presented in this paper highlights the tremendous potential and practical implications of these technologies in the realm of educational security.

Keywords: computer vision, digital twins, security, education institutions, machine learning, modeling.

Introduction

Ensuring the safety and security of educational institutions is of paramount importance. In recent years, advancements in computer vision technology and the development of virtual twins have provided new avenues for enhancing security measures within such environments. This paper aims to explore the potential applications of computer vision and virtual twins

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in the context of educational institutions, focusing on the development of a virtual twin of a school's first floor and its integration with a person detection algorithm. By leveraging real-time monitoring and comprehensive data analysis, the digital twin offers a powerful tool for enhancing security operations and facilitating prompt response to potential threats. Additionally, the study highlights the possibilities of training neural networks for specific security tasks, allowing for the identification of weapons or anomalies in human behavior. Through this research, we aim to contribute to the growing body of knowledge on leveraging technology for public safety in educational institutions.

Currently, there are numerous examples of digital twins being used for monitoring internal processes and optimizing them. Additionally, virtual twins are employed to simulate the behavior of existing infrastructure. These virtual twins accurately replicate the behavior of real objects and closely resemble them visually. They find applications in various fields such as medicine, industry, and smart cities.

In medicine, virtual twins are used to predict the effects of drugs on the body or the outcomes of surgeries for example, it was used in modeling brain dynamics after tumor resection using a virtual brain [1]. In the industrial sector, they facilitate the rapid testing of new products, equipment, and manufacturing methods [2]. In smart cities, virtual twins aid in city planning, management, and the development of effective public policies [3].

The key distinction between virtual twins and digital twins lies in their functionality. Virtual twins predict the behavior of simulated structures, while digital twins precisely replicate real-time processes. Digital twins are beneficial for monitoring and responding to situations as they unfold. To leverage the advantages of both virtual and digital twins, a combined approach can be adopted. For example, creating a virtual model of a structure with realistic objects and integrating real-time monitoring. By incorporating elements like neural networks for object detection, the functionality of virtual twins can be enhanced for real-time security. The realistic three-dimensional model of the structure provides a visually accurate representation of potential dangers, simplifying the monitoring process.

Literature Review

There are many use cases of using digital twin as a method for safety management in various industries. The [4] provides a comprehensive review of the current state-of-the-art in the application of digital twins for safety purposes. The authors present a thorough examination of various aspects related to the use of digital twins in ensuring safety across different domains.

The paper begins by introducing the concept of digital twins and their significance in safety-related applications. It highlights the potential benefits of digital twins, including real-time monitoring, predictive analysis, and risk assessment. The authors emphasize the importance of digital twins as a tool for enhancing safety measures in complex systems and environments.

The review covers a wide range of domains where digital twins have been applied for safety purposes, including manufacturing, healthcare, transportation, and energy. The authors discuss the specific applications of digital twins in each domain and provide examples of successful implementations. They delve into topics such as anomaly detection, fault diagnosis, process optimization, and decision support systems, showcasing the versatility and effectiveness of digital twins in ensuring safety.

One of the key strengths of this review is the comprehensive analysis of the challenges and limitations associated with digital twins for safety. The authors discuss issues related to data integration, model accuracy, scalability, and privacy concerns. They provide insights into the current research efforts and technological advancements aimed at addressing these challenges and improving the effectiveness of digital twins in safety applications.

Furthermore, the paper explores the integration of digital twins with emerging technologies such as Internet of Things (IoT), artificial intelligence (AI), and cloud computing. It discusses how these technologies complement and enhance the capabilities of digital twins in ensuring safety. The authors also highlight the importance of cybersecurity considerations in the implementation of digital twins for safety-critical systems.

Throughout the paper, the authors explore different digital twin applications that prioritize human-focused occupational safety. They discuss the use of digital twins for ergonomics analysis, human-machine interaction evaluation, and risk assessment. Examples of successful implementations in industries such as manufacturing, construction, healthcare, and transportation are provided.

One of the strengths of this review is its focus on the integration of real-time data and advanced sensing technologies with digital twins to monitor and analyze human behavior and well-being. The authors discuss the use of wearable devices, sensors, and physiological monitoring systems to capture relevant data and provide feedback to enhance occupational safety. They highlight the potential of digital twins in providing real-time risk warnings, predicting potential hazards, and enabling proactive safety measures.

The paper also addresses the challenges and limitations associated with human-focused digital twin applications for occupational safety. The authors discuss issues such as data privacy, model accuracy, system complexity, and user acceptance. They provide insights into ongoing research efforts and technological advancements aimed at addressing these challenges and improving the effectiveness of digital twin applications in ensuring occupational safety.

There are many other industries where digital twins play a significant role for applications. According to another paper [5], digital twins can be employed in the oil and gas industry for predictive maintenance, leading to improved safety by preventing accidents. This can help to prevent accidents and improve safety.

A Case Study [6], the authors present a case study highlighting the application of digital twins to improve safety in the mining industry. The study focuses on a coal mine and demonstrates how digital twins can effectively identify and mitigate hazards, thereby enhancing safety measures.

Kaewunruen, AbdelHadi, Kongpuang, Pansuk and Remennikov [7] examine the application of digital twins for railway safety in their paper titled « Digital Twins for Managing Railway Bridge Maintenance, Resilience, and Climate Change Adaptation « The authors propose a framework that utilizes digital twins to identify and address potential hazards within railway systems. By leveraging real-time data and simulation models, digital twins can enhance safety practices and contribute to the overall reliability and efficiency of railway operations.

Another paper discusses the implementation of digital twins to improve safety in construction projects [8]. The authors present a case study of a tunnel construction project and demonstrate how digital twins can be used to identify and mitigate potential hazards. The study highlights the benefits of integrating digital twin technology into construction processes to enhance safety measures and reduce risks.

Overall, these papers provide valuable insights into the use of digital twins in various industries to enhance safety measures. They showcase the potential of digital twin technology in predicting maintenance needs, identifying and mitigating hazards, and improving safety practices across different sectors.

The aim and objectives of the study

Overview of machine learning technology and its applications in ensuring safety

Computer vision applications have become increasingly prevalent in the field of surveillance and security, offering advanced capabilities for monitoring, analyzing, and protecting

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various environments. Here are some key areas where computer vision is applied: Video Surveillance: Computer vision algorithms can analyze live or recorded video feeds to detect and track objects of interest, such as individuals, vehicles, or specific objects; Intrusion Detection: Computer vision can be used to monitor restricted areas and detect unauthorized access or intrusions; Facial Recognition: Facial recognition technology utilizes computer vision to identify and verify individuals based on their facial features; Object Recognition: Computer vision algorithms can recognize specific objects or patterns in surveillance footage, including weapons, suspicious packages, or other predefined objects; Anomaly Detection: By learning normal patterns and behaviors in a given environment, computer vision systems can identify anomalies or deviations from the norm; Crowd Monitoring: Computer vision can analyze video data to monitor crowd behavior, count the number of people in an area, or detect potential safety concerns within a crowd; License Plate Recognition: Computer vision techniques can be employed to read and recognize license plate numbers on vehicles.

Overview of the digital twin of the facility and its applications in ensuring safety

Digital twin technology has been increasingly used in various industries to enhance safety measures and mitigate risks. Here are some applications of digital twins in ensuring safety: Manufacturing and Industrial Safety: Digital twins can simulate and monitor manufacturing processes, equipment, and industrial environments in real-time; Infrastructure Safety: Digital twins can model and monitor critical infrastructure such as bridges, buildings, and transportation systems; Emergency Preparedness: Digital twins can be used to simulate and plan for emergency scenarios; Occupational Safety and Training: Digital twins can simulate work environments, providing virtual training and safety simulations for workers; Smart Cities and Public Safety: Digital twins can model and monitor urban environments, including traffic flow, public spaces, and critical infrastructure.

Overall, digital twins provide a virtual replica of physical systems, enabling continuous monitoring, analysis, and optimization of safety measures. By simulating and predicting potential risks and hazards, digital twins contribute to creating safer and more resilient environments across various industries.

Possibilities of using machine learning technology and a digital twin of the facility to ensure the safety of educational institutions in Kazakhstan.

Using machine learning technology and a digital twin of educational institutions can offer several possibilities to ensure safety in Kazakhstan. Here are some potential applications: Security Monitoring: Machine learning algorithms can analyze data from security cameras, access control systems, and other sensors within the educational facility's digital twin; Crowd Management: Machine learning can be used to analyze the digital twin's representation of the facility, including classrooms, corridors, and gathering areas; Emergency Response Planning: By integrating machine learning with the digital twin, educational institutions can simulate and plan for emergency scenarios such as fires, natural disasters, or security incidents; Predictive Maintenance: Machine learning algorithms can analyze data from sensors within the digital twin to predict maintenance needs and identify potential safety risks in advance; Safety Training and Education: The digital twin can serve as a platform for safety training and education programs.

By combining machine learning technology with a digital twin of educational institutions, Kazakhstan can enhance the safety measures in schools and universities. These technologies can contribute to improved security monitoring, optimized crowd management, better emergency response planning, proactive maintenance, and effective safety training for the educational community.

Examples of successful technology applications in other countries

Computer vision technology has found successful applications in various countries across the globe. Here are a few notable examples:

1. China's Smart Cities: China has been at the forefront of implementing computer vision technology for various applications. For instance, in the city of Shenzhen, computer vision is used for traffic management, pedestrian safety, and facial recognition-based surveillance. The city employs a vast network of surveillance cameras and advanced algorithms to monitor traffic flow, detect violations, and enhance overall safety and security. [9]

2. Singapore's Surveillance Systems: Singapore has leveraged computer vision for comprehensive surveillance systems. The country utilizes advanced video analytics to monitor public spaces, including transportation hubs, streets, and public buildings. The technology helps in detecting and preventing crimes, identifying traffic violations, and enhancing public safety. [10]

3. United Kingdom's CCTV Systems: The United Kingdom has extensively deployed computer vision technology in its closed-circuit television (CCTV) systems. These systems use computer vision algorithms to analyze video feeds from surveillance cameras, enabling real-time monitoring, automated threat detection, and proactive security measures. They have been effective in preventing crimes, identifying suspects, and ensuring public safety. [11]

4. United States' Airport Security: Computer vision is widely used in airport security systems in the United States. Advanced imaging systems based on computer vision algorithms can detect prohibited items or suspicious behavior in passenger screening processes. These technologies enhance security measures, improve threat detection capabilities, and expedite the screening process. [12]

5. South Korea's Traffic Management: South Korea has implemented computer vision technology for efficient traffic management. Computer vision algorithms are used to monitor traffic flow, detect congestion, and optimize traffic signal control systems. These applications help in reducing traffic congestion, improving road safety, and enhancing overall transportation efficiency. [13]

6. Hardware-software system «Sergek»: «Sergek» is an intelligent hardware-software system developed by Kazakhstani IT specialists from «Korkem Telecom» to enhance public safety in Astana. It utilizes video surveillance, analysis, and prediction to monitor and record law violations on the streets and roads, resulting in a significant decrease in the fatality rate of road traffic incidents. [14]

7. Chine social credit system: China's social credit system merges financial credit scores with a broader quantification of social and civic integrity, encompassing factors such as purchasing history, interpersonal relationships, and political activities. The system rewards compliance with the government's ideals and punishes deviation from them. While Western liberal democratic countries do not currently have similarly unified systems, this article explores the existing structures and cultures of social media use and highlights the need for stricter data use policies to prevent a future resembling China's social credit system. [15]

Risks and limitations of technology applications in educational institutions

While computer vision technology offers numerous benefits for enhancing safety in educational institutions, it's important to be aware of certain risks and limitations associated with its applications. The use of computer vision technology in educational institutions may raise privacy concerns, particularly when it involves capturing and analyzing visual data of students, staff, or visitors. Computer vision algorithms are trained using large datasets, which can inadvertently include biases and reinforce discriminatory patterns. This can lead to inaccurate or biased outcomes, such as misidentification or profiling based on factors like race, gender, or appearance. Computer vision technology may have certain technical limitations that can

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affect its effectiveness. Factors such as lighting conditions, occlusions, or variations in camera angles can impact the accuracy of object detection or recognition. Computer vision algorithms are not infallible and can produce false positives (identifying something as a threat when it is not) or false negatives (failing to detect a potential threat). Educational institutions need to ensure that computer vision technology is used ethically and responsibly. Implementing computer vision systems in educational institutions may involve significant costs, including the installation of cameras, infrastructure upgrades, and ongoing maintenance.

It is important for educational institutions to be mindful of these risks and limitations and take appropriate measures to address them. This involves thorough planning, policy development, and ongoing evaluation to ensure the responsible and effective use of computer vision technology in the educational environment.

Mathematical model

For object detection from an image sequence, we need computer vision algorithm. The mathematical model of the algorithm can be formulated as follows:

Given an input image X of size $\mathrm{H} \times \mathrm{W}$ (height x width), where each pixel location (i, j) has a set of features $x(i, j)$ (RGB color values), want

$$\hat{Y} = P(X, Y)$$

where

$X = \{img(i,j) |\, img(i,j) \in \{0, 255\}\ for\ all\ 3\ channels\}$ – input image,

$Y = \big\{[x(i), y(i), w(i), h(i), C(i), p_i(c)] \in \{0,1\}\big\}$ – ground truth,

$\hat{Y} = \big\{[\hat{x}(i), \hat{y}(i), \widehat{w}(i), \hat{h}(i), \hat{C}(i), \hat{p}_i(c)] \in \{0,1\}\big\}$ – prediction.

x, y, w, h – coordinates (x, y) and size (w, y) of predicted bounding box, C – predicted class, $p(c)$ – confidence score for predicted class.

The function F is represented by a convolutional neural network (CNN) and is trained by minimizing a loss function that measures the discrepancy between the prediction and ground truth, often computed on a per-pixel basis:

$$\lambda_{coord} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \zeta_{ij}^{obj} [(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2] + \lambda_{coord} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \zeta_{ij}^{obj} \left[(w_i - \widehat{w}_i)^2 + \left(h_i - \hat{h}_i\right)^2\right]$$
$$+ \sum_{i=0}^{S^2} \sum_{j=0}^{B} \zeta_{ij}^{obj} \left(C_i - \hat{C}_i\right)^2 + \lambda_{noobj} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \zeta_{ij}^{noobj} \left(C_i - \hat{C}_i\right)^2 \quad (1)$$
$$+ \sum_{i=0}^{S^2} \zeta_{i}^{obj} \sum_{c \in classes} \left(p_i(c) - \hat{p}_i(c)\right)^2$$

where

$\zeta_{ij}^{obj} = 1$ if the j^{th} boundary box in cell i is responsible for detecting the object, otherwise 0,

$\zeta_{ij}^{obj} = 1$ if an object appears in cell i, otherwise 0,

ζ_{ij}^{noobj} is the complement of ζ_{ij}^{obj}

model uses sum-squared error between the predictions and the ground truth to calculate loss. The loss function composes of:

- localization loss (errors between the coordinates and sizes of the predicted boundary box and the ground truth).
- classification loss.
- confidence loss (the objectness of the box).

Materials and Methods

Digital Twin

As part of an intra-university project exploring the potential applications of computer vision algorithms, a digital twin of School No. 89 in Astana was developed in collaboration with the Department of Education of Astana. The floor plans of the school's first floor were provided by the school administration for the purpose of creating a digital representation.

Using Autodesk 3ds Max software, the interior spaces of the school's first floor were modeled based on the floor plans. The modeling task was carried out by a team of five second-year students from Astana IT University. The process of creating the digital twin followed a well-defined workflow "Fig. 1".

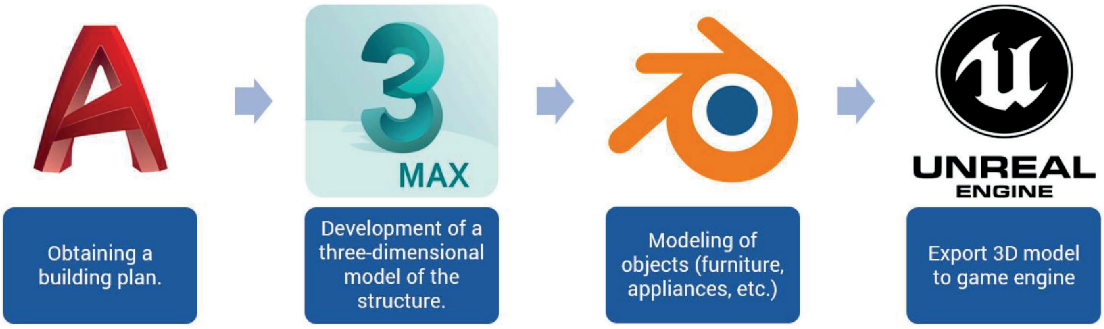

Figure 1. Various stages involved in working with the software.

Different modeling techniques were employed depending on the shape and characteristics of the objects. Spline modeling was utilized to create three-dimensional models of walls and partitions within the school, while polygonal modeling was employed for furniture items. Spline modeling involves defining splines that traverse the external surfaces of walls, thereby outlining the perimeters of all walls and partitions. These splines are then extruded using the Extrude modifier.

On the other hand, polygonal modeling entails constructing a mesh composed of triangular polygons that closely replicate the shape and structure of the modeled objects. The first floor of the school encompasses an area of 1400 square meters, comprising more than 30 classrooms and various rooms "Fig. 2". All models were crafted with precise adherence to real-world dimensions, maintaining a 1:1 scale representation.

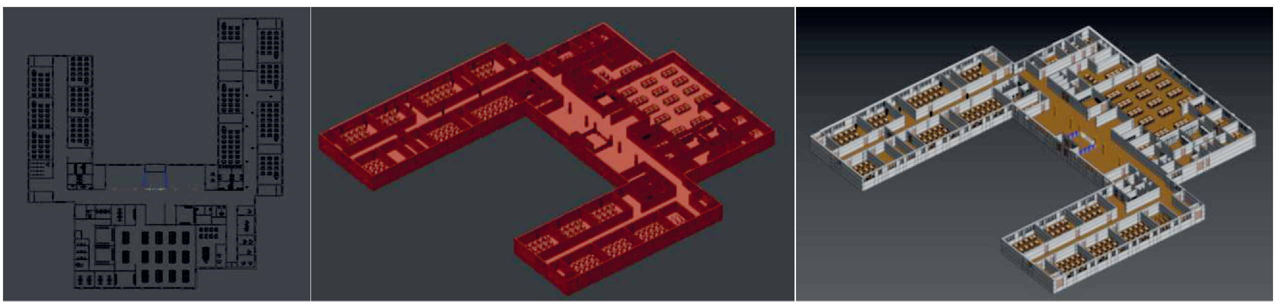

Figure 2. School building plan, modeling and texturing

Following the completion of the modeling process, the three-dimensional model was exported to the Unreal Engine game engine using the official Datasmith Importer plugin specifically designed for Autodesk 3ds Max. This plugin facilitates the seamless transfer of all

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dimensional data, coordinate systems, and applied materials to Unreal Engine, ensuring a smooth integration without encountering any technical difficulties.

Computer vision algorithms

There are several algorithms for object detection. Object detection algorithms are a fundamental part of computer vision and are used to identify and locate objects within digital images or video frames. Here are some popular object detection algorithms that works on real-time: Faster R-CNN (Region-based Convolutional Neural Networks) [16], You Only Look Once (YOLO) [17], Single Shot MultiBox Detector (SSD) [18], Mask R-CNN [19]

There are several less popular types of object detection algorithms, such as Histogram of Oriented Gradients (HOG [20], Selective Search [21].

The YOLOV8 algorithm was chosen for the task as it demonstrates the highest Mean Average Precision (mAP) scores and operates in real-time. Mean Average Precision (mAP): mAP is a popular metric for object detection and is calculated by averaging the AP across different object categories. It provides an overall measure of the model's performance across multiple classes. YOLOv8 has achieved a remarkable milestone in the history of the YOLO algorithm by achieving the highest Mean Average Precision (mAP) of 53.9. This achievement represents a significant improvement in the accuracy and performance of the YOLO series of object detection models "Fig. 3".

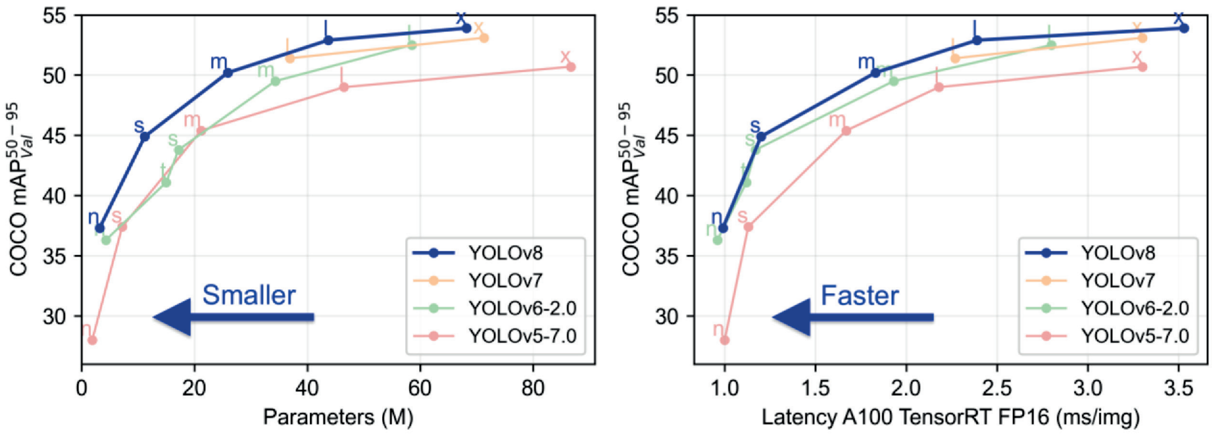

Figure 3. Comparison of different YOLO series

YOLOv8, or You Only Look Once version 8, is an object detection algorithm that builds upon the YOLO architecture. It improves upon its predecessors, such as YOLOv4 and YOLOv3, by incorporating several enhancements.

By leveraging these techniques, YOLOv8 aims to achieve real-time or near real-time object detection while maintaining competitive accuracy. It combines the advantages of single-shot detection, multi-scale processing, anchor boxes, and efficient network architectures to enable efficient and effective object detection in various applications.

Data preparation

Before object detection can be performed on the video stream, it is necessary to correct for its radial distortion, which is commonly present in most surveillance cameras. To achieve this, the calibration coefficients of the surveillance camera need to be determined. These coefficients are determined using the Zhang's method [22].

When calibrating a fisheye camera, one commonly used algorithm is the Zhang's method, which is an extension of the standard camera calibration algorithm proposed by Zhang

Zhengyou. This algorithm can estimate the intrinsic camera parameters and distortion coefficients specific to fisheye lenses. Here is an overview of the steps involved: Image capture: Capture a set of calibration images of a calibration pattern (e.g., chessboard) using the fisheye camera; Chessboard corner detection: Detect the corners of the calibration pattern in the captured images; Corner extraction: Extract the detected corner coordinates from the images; Initialization: Initialize the camera intrinsic parameters, including the focal length, principal point, and distortion coefficients; Optimization: Optimize the initial parameters by minimizing the reprojection error; Distortion model: Fisheye lenses introduce significant radial distortion; Refinement: Iterate the optimization process, refining the intrinsic parameters and distortion coefficients until convergence is achieved or a desired level of accuracy is reached; Calibration evaluation: Assess the calibration quality by examining the reprojection errors and checking how well the calibrated model aligns the detected corner points with the known 3D world coordinates; Validation: Validate the calibrated camera model by capturing additional images and verifying the accuracy of the pose estimation and distortion correction.

By following these steps, the Zhang's method, adapted for fisheye cameras, can estimate the calibration coefficients that accurately characterize the intrinsic parameters and distortion of the fisheye lens, enabling accurate image analysis and processing.

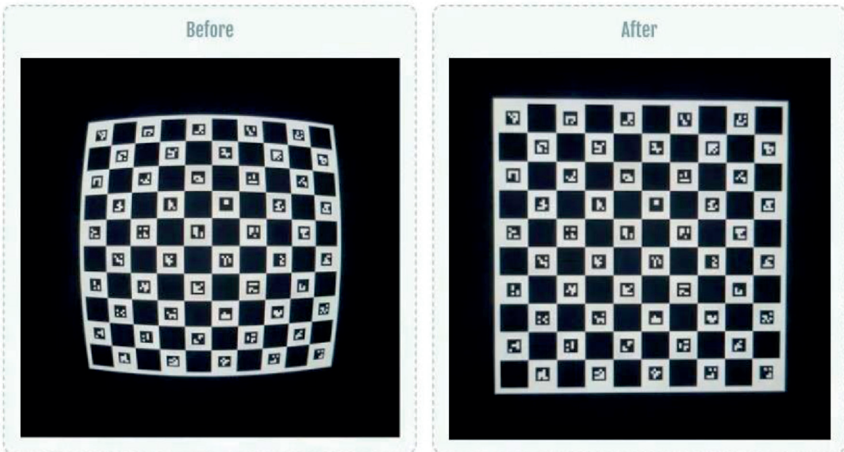

Figure 4. Chess board before and after camera distortion correction

To accomplish this, we need to download an image of a chessboard and take 5-6 pictures using the camera you want to process. All images should be converted to the PNG format. Next, we execute the algorithm for determining the calibration coefficients. As a result of running this script, a message will appear in the console indicating the processed photos, and two important parameters will be displayed: the camera matrix and distortion coefficients. These are the calibration coefficients we need.

However, the obtained data from the video stream is insufficient for determining a person's location. To achieve this, the obtained coordinates from the video stream need to be transformed into top-view coordinates. Therefore, the coordinates undergo a perspective transformation algorithm. The essence of the algorithm lies in transforming the coordinates using four points that form the vertices of a quadrilateral.

To create a top-down perspective effect on a video recorded from a surveillance camera, we utilized a technique called homography transformation "Fig. 5". Homography transformation allows you to map points from one perspective to another perspective, effectively changing the viewpoint of the video [20].

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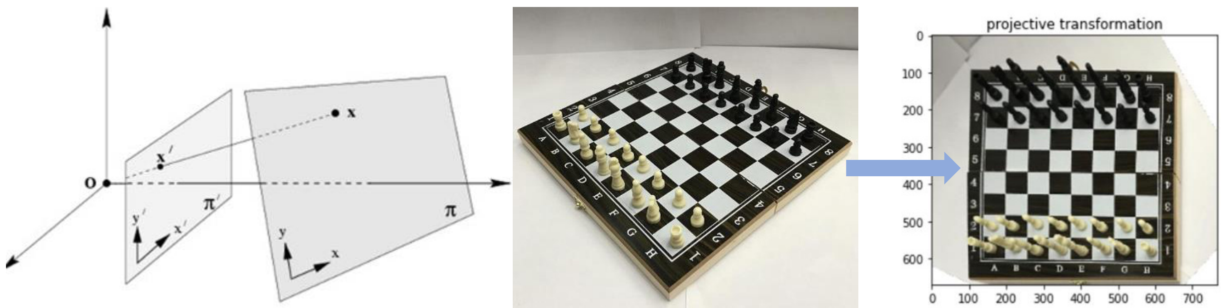
A homography, also known as a planar homography, is a transformation that relates two different planes. Essentially, it represents a mapping between two planar projections of an image [23]. The homography is represented using a 3x3 transformation matrix in a homogeneous coordinate system. In mathematical terms, the homography matrix is expressed as follows:

$$s\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = H\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix}\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \quad (2)$$

In the illustration "Fig. 5a", you can see that an element present in one image is projected onto the other image using homogeneous coordinates. This transformation preserves the information of the element but presents it from a different perspective due to the transformation applied by the homography.



a) b)

Figure 5. a) image projection to the other image. b) an example of the operation of the position determination algorithm

Specified 4 points for each video stream, forming a rectangle and creating a top-view perspective "Fig. 5b". The coordinates are determined relative to the top-left corner. All obtained coordinates have been stored in a database. The number of individuals in each frame can vary, making it impossible to store the coordinates of each object in a separate cell, as altering the number of columns in the table for each frame is also not feasible. Therefore, the coordinates were concatenated into a single string with a semicolon delimiter and saved in a single cell of the table. This ensures that the table structure remains unchanged.

Figure 6. Position determination algorithm on real data from school

Connecting the Algorithm to the Virtual Model

The algorithm records real-time data into a database. It is necessary to transmit this data to the digital twin of the structure in real-time. To achieve this, an API has been developed to retrieve the latest data from the database and send it to the digital twin. The Flask library for Python was utilized for implementing the API. The algorithm receives a request with the identifier of a specific camera and transfers the corresponding data from the database as a single string to the digital twin "Fig. 7".

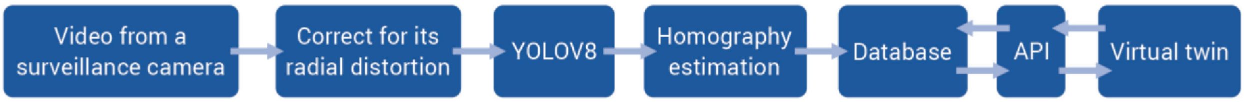


Figure 7. Process of virtual twin and real data connection

The digital twin was created using the Unreal Engine platform, a game engine developed and maintained by Epic Games. The VaRest plugin for Unreal Engine was employed to establish the connection with the API. The algorithm operates as follows: the received API string is converted into a data array using a semicolon as a delimiter. Each element of the array represents a string containing top-view coordinates. Subsequently, this element is transformed into X and Y coordinates. As a result, an array of coordinates for each object from the latest video frame is obtained "Fig. 7". Based on these coordinates, a three-dimensional object is created to represent a person. Each time the algorithm is executed, all previously created three-dimensional person objects in the digital twin are removed and replaced with new ones based on the latest received coordinates. The frequency of data retrieval by the algorithm can be adjusted.

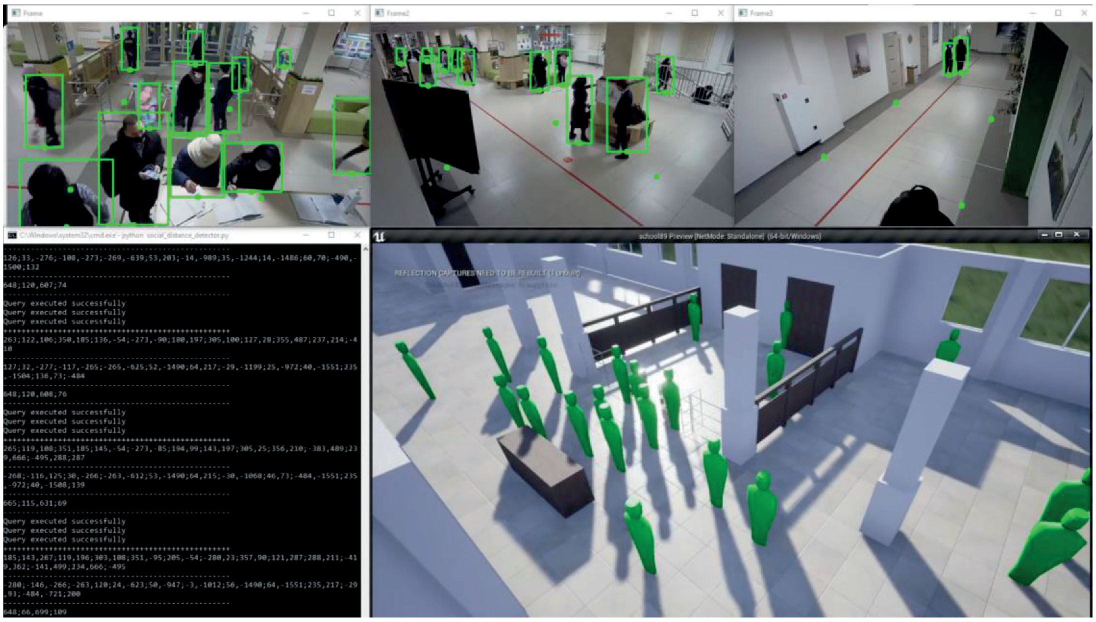


Figure 8. Results of virtual twin and real data connection Process on real-time

Results

As a result of our work, we obtained a digital twin of the school with real-time monitoring of people's locations [14]. The person detection algorithm was integrated with the surveillance cameras. Each camera has its designated monitoring zone, and the camera data, as well as the camera itself, are recorded in the database in a specific format. A virtual replica of the school's first floor was created for testing purposes. The model was developed using multiple software tools and visualized in the Unreal Engine game engine. An API was created to retrieve data from the database. Based on the received coordinates, person models are generated within the digital twin to represent individuals. Consequently, we successfully connected the neural network model to the digital twin, enabling comprehensive monitoring of the entire premises within a single model, thereby simplifying security operations.

Conclusion

In conclusion, the use of virtual twins and digital twins offers significant potential for enhancing security across various domains. Virtual twins, with their ability to simulate and predict the behavior of existing infrastructure, provide valuable insights for proactive security measures. On the other hand, digital twins, replicating real-time processes, enable monitoring and immediate response to security incidents. By combining the strengths of both virtual and digital twins, a comprehensive approach can be achieved, facilitating real-time security monitoring with realistic visual representation.

The examples provided highlight the successful applications of digital twins and virtual twins in different sectors, including manufacturing, smart cities, healthcare, and more. These applications demonstrate the effectiveness of digital twins for optimizing processes, improving decision-making, and mitigating risks. Additionally, virtual twins offer the advantage of simulating complex scenarios, enabling advanced planning, and enhancing security preparedness.

However, it is important to address challenges and considerations associated with the adoption of twin technologies. Privacy concerns, data security, and ethical implications need to be carefully addressed to ensure the responsible and secure implementation of twin technologies.

Our experience demonstrates the potential application of other neural networks in security measures using the digital twin of a building. This includes the ability to train the neural network for specific tasks. For example, it is possible to train the network to identify weapons or suspicious objects instead of humans, which may be more relevant in certain scenarios. There are also neural networks capable of detecting anomalies in human behavior. All these models can be integrated into the digital twin of any facility, facilitating the task of ensuring public safety.

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Reference

1. Wang, H.E., Scholly, J., Triebkorn, P., Sip, V., Medina Villalon, S., Woodman, M.M., Le Troter, A., Guye, M., Bartolomei, F., & Jirsa, V. (2021). VEP atlas: An anatomic and functional human brain atlas dedicated to epilepsy patients. *Journal of Neuroscience Methods, 348*, 108983. https://doi.org/10.1016/j.jneumeth.2020.108983
2. Liu, M., Fang, S., Dong, H., & Xu, C. (2021). Review of digital twin about concepts, technologies, and industrial applications. *Journal of Manufacturing Systems, 58*, 346–361. https://doi.org/10.1016/j.jmsy.2020.06.017
3. Allam, Z., Sharifi, A., Bibri, S.E., Jones, D.S., & Krogstie, J. (2022). The Metaverse as a virtual form of smart cities: Opportunities and challenges for environmental, economic, and social sustainability in urban futures. *Smart Cities, 5*(3), 771–801. https://doi.org/10.3390/smartcities5030040
4. Park, J.-S., Lee, D.-G., Jimenez, J.A., Lee, S.-J., & Kim, J.-W. (2023). Human-focused digital twin applications for occupational safety and health in workplaces: A brief survey and research directions. *Applied Sciences, 13*(7), 4598. https://doi.org/10.3390/app13074598

5. Wanasinghe, T.R., Wroblewski, L., Petersen, B.K., Gosine, R.G., James, L.A., De Silva, O., Mann, G.K.I., & Warrian, P.J. (2020). Digital twin for the oil and gas industry: Overview, research trends, opportunities, and challenges. *IEEE Access, 8*, 104175–104197. https://doi.org/10.1109/access.2020.2998723
6. Wang, J., Huang, Y., Zhai, W., Li, J., Ouyang, S., Gao, H., Liu, Y., & Wang, G. (2023). Research on coal mine safety management based on digital twin. *Heliyon, 9*(3), e13608. https://doi.org/10.1016/j.heliyon.2023.e13608
7. Kaewunruen, S., AbdelHadi, M., Kongpuang, M., Pansuk, W., & Remennikov, A.M. (2022). Digital twins for managing railway bridge maintenance, resilience, and climate change adaptation. *Sensors, 23*(1), 252. https://doi.org/10.3390/s23010252
8. Salem, T., & Dragomir, M. (2023). Digital twins for construction projects—Developing a risk systematization approach to facilitate anomaly detection in smart buildings. *Telecom, 4*(1), 135–145. https://doi.org/10.3390/telecom4010009
9. Shan, Z., Zhang, Y., Zhang, Y., Tang, S., & Wang, W. (2021). A review of recent progress and developments in China smart cities. *IET Smart Cities, 3*(4), 189–200. https://doi.org/10.1049/smc2.12020
10. Jason Shueh. (2017). Smart city surveillance: Singapore's camera system stands as a potent deterrent. Statescoop. https://statescoop.com/smart-city-surveillance-singapores-camera-system-stands-as-a-potent-deterrent/
11. Gentile, G. (2023). Does Big Brother exist? Face recognition technology in the United Kingdom. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4331633
12. Liang, K.J., Sigman, J.B., Spell, G.P., Strellis, D., Chang, W., Liu, F., Mehta, T., & Carin, L. (2019). Toward automatic threat recognition for airport X-ray baggage screening with deep convolutional object detection (Version 1). arXiv. https://doi.org/10.48550/ARXIV.1912.06329
13. Lee, C., Kim, Y., Jin, S., Kim, D., Maciejewski, R., Ebert, D., & Ko, S. (2020). A visual analytics system for exploring, monitoring, and forecasting road traffic congestion. *IEEE Transactions on Visualization and Computer Graphics, 26*(11), 3133–3146. https://doi.org/10.1109/tvcg.2019.2922597
14. Enelane, N. (2018). Kak rabotaet proekt «Sergek». Reportazh Informburo.kz. Retrieved from *Informburo* website: https://informburo.kz/stati/kak-rabotaet-proekt-sergek-reportazh-informburokz.html.
15. Wong, K.L.X., & Dobson, A.S. (2019). We're just data: Exploring China's social credit system in relation to digital platform ratings cultures in Westernised democracies. *Global Media and China, 4*(2), 220–232. https://doi.org/10.1177/2059436419856090.
16. Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks (Version 3). *arXiv*. https://doi.org/10.48550/ARXIV.1506.01497.
17. Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2015). You Only Look Once: Unified, Real-Time Object Detection (Version 5). *arXiv*. https://doi.org/10.48550/ARXIV.1506.02640.
18. Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C.-Y., & Berg, A. C. (2016). SSD: Single Shot MultiBox Detector. In *Computer Vision – ECCV 2016* (pp. 21–37). Springer International Publishing. https://doi.org/10.1007/978-3-319-46448-0_2.
19. He, K., Gkioxari, G., Dollár, P., & Girshick, R. (2017). Mask R-CNN (Version 3). *arXiv*. https://doi.org/10.48550/ARXIV.1703.06870.
20. Dalal, N., & Triggs, B. (n.d.). Histograms of Oriented Gradients for Human Detection. In *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)*. IEEE. https://doi.org/10.1109/cvpr.2005.177.
21. Uijlings, J.R.R., van de Sande, K.E.A., Gevers, T., & Smeulders, A.W.M. (2013). Selective Search for Object Recognition. *International Journal of Computer Vision, 104*(2), 154–171. Springer Science and Business Media LLC. https://doi.org/10.1007/s11263-013-0620-5.
22. Chan, S., Zhou, X., Huang, C., Chen, S., & Li, Y.F. (2016). An improved method for fisheye camera calibration and distortion correction. In *2016 International Conference on Advanced Robotics and Mechatronics (ICARM)*. IEEE. https://doi.org/10.1109/icarm.2016.7606985.
23. Sung, Thaileang & Lee, Hyo Jong. (2018). Images Alignment Using Homography Transformation Matrix.
24. A-square. (2022, December 4). Using a virtual twin of a building in educational institutions [Video]. *YouTube*. https://youtu.be/ORjfedZs88A.

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