# Video Surveillance Architecture at the Edge

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**Abstract**

This paper examines the use of digital video in public safety and surveillance systems. Traditionally video recordings are used by law enforcement to review events retrospectively and for evidential purposes in the pursuance of criminal prosecution. We also examine how, due to the proliferation of cameras around cities, human operators are challenged to monitor these data feeds in real-time and how the emergence of AI and computer vision solutions can process this data. Computer vision can enable the move from a purely reactive to a predictive, real-time analysis platform. As camera numbers and the resolution and framerate of cameras grow, existing network infrastructure frequently causes challenges provisioning low latency, high bandwidth networking to private or public cloud infrastructure for evidential storage. These technical challenges can provide issues for law enforcement providing a data chain of custody to ensure its admissibility during court proceedings. Emerging technologies offer solutions to overcome these challenges: the use of emerging edge compute capabilities, including the use of on-camera and mobile edge compute nodes providing compute capabilities closer to the data source and new software paradigms, including CI/CD methodologies, and the use of micro-services and containerization to manage and deliver applications across the portfolio of devices, at the edge of the network.

## 1 Introduction

The use of closed-circuit television systems (CCTV) has its roots in the 1940s, with the first documented use of CCTV systems in Durham, UK, in 1956 [1]. This system enabled a police officer to monitor and operate traffic lights. The use of cameras in law enforcement has been, to date, mainly for evidential purposes, with data stored and then manually reviewed post-incident by CCTV operators. The migration from magnetic tape recordings to digital media stored on centralized computer systems has enabled the deployment of surveillance cameras at a much higher density than would have been possible previously.

The challenges of transporting data to the cloud for processing have long been acknowledged as problematic, especially for large datasets such as streaming video. On cloud platforms, Network latency is the primary challenge to processing streaming data in real-time [2]. Numerous methods of moving compute closer to the data source have been proposed to alleviate this latency, including

Fog[3], Cloudlets [4] and Edge computing. Lin, et al. [5] discuss the difference between edge and fog computing: *"edge computing builds the architecture of computing at the edge, while fog computing uses edge computing and further defines the network connection over edge devices, edge servers, and the cloud."* These edge devices can provide traditional CPU and accelerator compute capabilities to enable computer vision code to run on resource-constrained edge devices. On-camera compute already provides significant bandwidth reductions in several use cases including motion detection and automatic number plate recognition[6]. The camera then only returns metadata, along with an evidential photograph of a speeding car, rather than a full video stream from the cameras to be processed in the cloud. By processing on the camera, both network traffic and the amount of storage required in the system[7] are reduced compared to traditional evidential recording platforms. To deliver timely, predictive and proactive computer vision analytics platforms, the design of conventional evidential recording systems needs to be reviewed to move the compute capabilities closer to the source of the data.

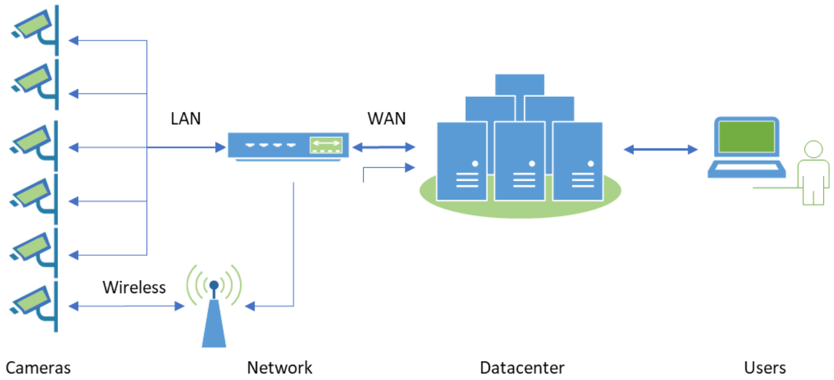



**Figure 1:** Evidential Recording Infrastructure

# 2 Evidential Recording Platforms

To provide evidence for law enforcement agencies after an incident and provide a chain of custody of video footage to be used in prosecutions, Digital (DVR) or Network (NVR) video recording systems provide a platform to deploy and manage the cameras and storage of the data they create. The systems also include management structures for the stored data to ensure storing, access and deletion according to legal data governance requirements. Centrally managed digital surveillance systems have several key platform components, described in Figure 1 above.

## 2.1 Cameras

The first digital IP cameras became commercially available in 1996, with the release of Axis Communications Neteye 200 camera [8], which supported a resolution of 352x288 pixels at a frame rate of 1 frame per second (FPS) in JPEG format [9]. Currently, the most popular resolution for digital surveillance systems is full HD (1920x1080), producing uncompressed data streams of up to 1.5Gbit/S[10]. Using H.264/AVC compression reduces this data stream by up to 70%. As H.264/AVC is an asymmetric process, with more compute required at the encoder than at the decoder [11], onboard microprocessors in cameras have evolved in parallel with the image sensor capabilities, with CPU, GPU & FGPA capabilities or by a specialist Digital Signal Processor (DSPs) [12]. Alongside compression, the compute capabilities also provide remote management capabilities, essential for large suites of cameras. The ONVIF [13] specification for camera management is included in published standards, such as IEC 62676, for Video Surveillance Systems.

## 2.2 Network

Digital surveillance cameras have standardized TCP/IP over ethernet and generally use IEEE standard 802.3u (Fast Ethernet/ 100Base-T). As TCP/IP is bi-directional, it also enables the management and manipulation of Point, Tilt & Zoom (PTZ) cameras movement controls [14] without the need for secondary cabling. Cameras connect to local area network (LAN) switches, which can also act as power sourcing equipment to provide power and data to cameras via one cable, using IEEE 802.3a(x) standards [15]. The use of Wi-Fi for surveillance systems to connect static cameras, using IEEE 802.11 is used in limited circumstances but provides range, reliability, and security challenges for critical systems. [16], but Wi-Fi and 4G cellular connectivity are widely utilized for body-worn and mobile/vehicle cameras[17]; however, these devices frequently have localized storage to overcome connectivity issues and limited recording periods due to battery charge longevity[18]. Backhaul to the datacenter is dependent upon each installation, with fully private fiber networks utilized in very high-security environments or built upon virtual private networks (VPN) provided by 3rd party telecom providers, with networking and security capabilities such as NAT, Firewalls, and VPN Tunnels used to protect the transmission of the data.[19] The ESTI standard for TErrestrial Trunked RAdio (TETRA) provides a data carrier protocol, with up to 600mbps throughput, to provide fully encrypted, secure communications but requires a separate infrastructure for broadcasting capabilities, aside from regular telco operated environments. One of the significant examples of the use of TETRA in surveillance was its use at the Athens Olympics, where feeds from live CCTV cameras were broadcast via Tetra to security/law enforcement officers handsets on the ground [20].

## 2.3 Datacenter

The core of all video surveillance systems is the network video recording (NVR) system, with leading providers including Milestone Systems, Avigilon, Bosch, Huawei and Genetec [21]. The NVR provides a range of features, including management of the cameras, storage management, including writing data to storage, and managing data, ensuring timely deletion, the chain of custody reporting, and access for users to review the recorded footage.

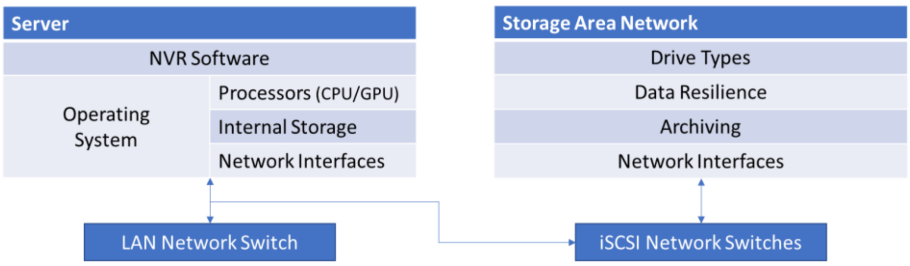



**Figure 2:** NVR Architecture

Servers are predominantly Intel x86 platforms, with many NVR providers using Microsoft Windows© Server or Linux operating systems. Depending on the scale of requirements, storage may be anything from a single hard disk to a complete server & storage area network configuration, as shown in Figure 2 above. Storage Area Networks (SAN) provide network-attached storage, using iSCSI, or Fiber-channel over IP connectivity with Redundant Array of Inexpensive Disks (RAID) offering fault-tolerant, highly scalable storage platforms for storage and data throughput capabilities[22]. Disk configuration is dependent on several factors from the dataflow: the number of cameras, frame resolution & speed; motion detection; compression algorithms; the number of days storage, expected activity levels in the cameras[23, 24] and the hardware in the SAN, including the number of disks, IOPs for each disk, RAID or other redundancy/data protection systems and SAN processor speed.

## 2.4 Users

Users require a method of accessing the stored data, either from individual cameras or in Command & Control walls with multiple screens, with thumbnail streaming video images of multiple cameras displaying concurrently, with the ability for the user to click into one of the thumbnails and maximize screens of interest. The NVR software also provides the user with methods to view historical material and protect the material of interest against overwriting by the NVR storage management schedule. User feeds are delivered to a proprietary application running on a personal computer or via HTTP/s web browser. NVR Manufacturers recommend that the user workstation provide substantial processing power, both from the CPU and Graphics Processing Unit (GPU), with 8GB RAM and a 64-bit Windows operating system, to deliver a satisfactory user experience significant numbers of camera feeds on screen [25, 26].

# 3 Video Analysis Platforms

The UK has led the global growth of surveillance [27], with over 500,000 cameras in London and 15,000 on the Underground alone. Research shows that video surveillance was useful to investigators in some 29% of crimes committed on the British transport systems [28]. With the proliferation of cameras for surveillance purposes, it is impossible to monitor video feeds in real-time. Alongside the growth of surveillance systems, the rise of computer vision technologies built upon research in artificial intelligence (AI) has provided the building blocks for video analysis. Using large previously labelled sets of data to train the convolutional neural networks (CNN) [29, 30] built upon deep neural networks (DNN) [31] before deployment to analyze real-time video feeds. AI-enabled video analysis provides evidential data and provides opportunities for law enforcement to offer proactive capabilities using motion detection, facial recognition, individual and crowd behavior analysis.

The software stack must provide the ability to allow developers to build scalable, manageable software platforms that can be remotely managed. Microservices container-based platforms such as Docker, Openstack and container management such as Kubernetes [32] and K3S [33] for resource-constrained hardware provide the infrastructure and management layers. Open-source toolkits such as YoLo provide a convolutional network framework for image recognition, [34] and Edge-X from the Linux Foundation provides an IIoT platform framework, to enable this scalability.

One of the challenges called out by Sada, et al. [35] in edge video analysis is the fragmentation of the original inference model across edge devices. They propose a federated learning platform for CNN across edge devices. Li, et al. [36] describe federated analytics as *"decentralized privacy-preserving technology to overcome challenges of data silos and data sensibility."* Deng, et al. [37] propose a federated system using Neural networks spanning from the video cameras to mobile edge compute capabilities and an edge optimization capability, thereby optimizing latency and accuracy of queries to a video analytics system.

As camera resolution increases, H.264/AVC becomes less efficient, and H.265/HEVC provides a decrease the size of the bitstream by at least 50% compared to H.264/AVC, whilst supporting resolutions up to 8192x4320 with equivalent quality to H.264 [38, 39]. Tan, et al. [40] report up to 64% H.265/HEVC Bitrate deduction vs H.264/AVC for the same resolutions. H.265/HEVC does come with increased computational overheads. Sullivan, et al. [39] estimate that with more modern computing capabilities, the 40% increase in processing requirements over H.264/AVC for encoding is not a significant constraint for new equipment, but the existing install base of cameras will continue to use H.264/AVC due to compute constraints of the hardware[41]

## 3.1 Cloud video analytics

Alam, et al. [42] discusses the benefits of cloud computing and its ability to deliver platform, software, and infrastructure as a service to users. Research has identified several areas of challenges to processing streaming video analysis in the cloud. Three of the major industries using computer vision are autonomous vehicles, manufacturing and sport [43]. Mach and Becvar [44] identify some challenges of cloud computing. These technical challenges can be aligned into three main areas: connectivity, latency and security [45]. They are well documented in different vertical industries, as identified in Table 1 below.

**Table 1** Cloud Computing Challenges

| | |
|---|---|
| Connectivity | Sporadically connected devices and the use of streaming video data (along with lidar and radar) in autonomous vehicles to enable object detection[46], platooning [47], or to enable parking in cities [48] require reliable connectivity to the cloud. Environments with high levels of radio interference, such as manufacturing facilities [49] provide challenges to connect to cloud infrastructures. |
| Latency | Autonomous vehicles are highly dependent on reliable, low-latency communication, with round trip response times of under 100ms required due to the high speeds of the vehicles, especially in the realms of object detection and avoidance, and in interaction with other vehicles, such as intersection management[50]. The use of cloud analysis in the area of sports analysis, to provide statistics that can be used for presentation purposes [51] is well established. The framerate required by cameras to enable Goal Line monitoring requires localized compute to provide the referee with timely and accurate analysis and information [52]. Wireless connectivity using LTE and Wi-Fi [53] to the cloud also presents challenges where sub 100ms response times are required. |
| Security | The security of data flowing to the cloud, both in transit and at the final location are concerns for many cloud-based platforms. In Healthcare, patient confidentiality and protection of Individually Identifiable Health information is enshrined in standards (HIPPA, GDPR etc.) [54]. Liu, et al. [55] discusses the security requirements in vehicle to everything (V2X) autonomous vehicles in the realm of safety as the backbone to all autonomous vehicle systems. |

Research from the challenges associated with cloud processing of data has focused on moving compute closer to the data source and has resulted in the emergence of edge computing capabilities. Sunyaev [56] reviews the emergence of edge computing and identifies the key goals these platforms aim to provide, overcoming the challenges posed by processing workloads in the cloud. Areas of focus for edge computing are around the hardware platforms, connectivity, and management of software to these remote devices, and the use of artificial intelligence algorithms within the software to undertake computer vision workloads. With emerging connectivity capabilities offered by 5G and the evolution of Mobile Edge Compute (MEC), new workload management platforms for edge compute such as Docker (with Kubernetes management for large deployments across edge devices), the ability to process streaming data at the edge is moving forward. Zhou, et al. [57] review the capabilities of edge platforms for AI Models to run at the edge: *"hardware acceleration technologies, such as field-programmable gate arrays (FPGAs), graphical processing units (GPUs)".* Research by Najafi, et al. [58] suggests Application-specific integrated circuits (ASICs) offer significant promise for accelerating video analysis edge computing, and the use of smart network interface cards (SmartNiC) enables the offload of tasks from the computing platform. Emerging technologies, such as neuromorphic computing, look to overcome some challenges traditional edge hardware platforms are constrained by[59].

## 3.2 Edge video analytics

Moving the analytical processing of the image closer to the camera, or even onto it, can increase the performance of a system. This is especially evident where connectivity is limited or unreliable, or information from the processed data is deemed to be time-sensitive and is to be consumed at the edge, for example, real-time management of relays for complex traffic light systems. Processing can be either on the camera, Mobile Edge Compute platforms, or the cloud. The hardware required to enable a computer vision system has several separate components, outlined in table 2 below, from the compute on the camera delivering specific tasks such as ANPR or motion detection using CNNs, or edge compute devices, the use of MEC to analyze data from multiple local cameras, backend cloud platform compute capabilities, with access to historical data sets for deep learning algorithms to process, the latency of the networks, and the compute capacity, in terms of memory and processor capabilities at each node in the infrastructure all play a role in identifying where the most efficient location to undertake the compute.

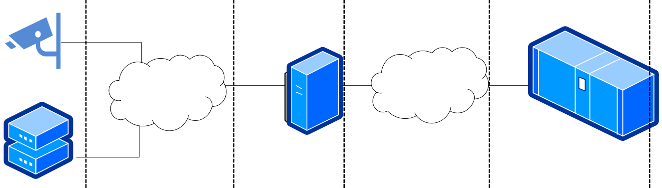
| Characteristics | Edge | LTE/5G | MEC | WAN | Cloud |
|---|---|---|---|---|---|
| |  | | | | |
| Network Latency | | 100ms+ | | 75ms | |
| GPU Cores | 240 | | 5120 | | 20,480 |
| Data set Scale | GB | | TB | | PB |

**Table 2:** Processing Matrix in Machine Vision Systems

## 3.3 On Camera

Shi and Lichman [60] discuss cameras with "Application Specific Information Processing". The inbuilt microprocessors used to run code for specific purposes, such as motion and object detection, provide data to automated control systems. The benefits of onboard processing can reduce the bandwidth required to transmit the data from many megabits to several bytes, denoting motion or object detected. The first use of onboard compute within a camera was in the area of Motion detection. Whilst compression algorithms identify activity for prediction purposes, motion detection is used to determine the movement within the camera's view and trigger an action when identified. Sehairi, et al. [61] identified three separate categories of motion detection: Background Subtraction, Temporal Difference and Optical flow techniques, and evaluated the effectiveness of the differing algorithms. Challenges such as bad weather, thermal changes, vibration etc.[62] can cause difficulties for motion detection. Large bodies of work exist exploring the areas of false positive and false negative identification of motion detection.[63] As part of the processing of motion detection, cameras also allow for the masking of images. Masking allows regions of the image not of interest to the operator to be eliminated from processing, saving time and compute.[64] Automatic Numberplate Recognition (ANPR) or License Plate Recognition (LPR) have been in use extensively since the early 2000s [65]. They are based on Optical Character Recognition performed on video captured and streamed to a central video management system. Jeffrey, et al. [66] discuss the use of ARM-based processors and FPGAs to undertake ANPR on-camera analysis. With the increasing compute power on the camera, ANPR enabled camera algorithms can now provide descriptive feedback across the network (i.e. the number plate details), rather than just the video stream that would have to be further processed. Farhat, et al. [67] demonstrated that a Zynq-7000 programmable system on a chip (SoC) within a camera could provide ANPR recognition with a success rate of 99.5%, and with a power consumption rate 80% less than that of a Intel PC based platform undertaking the same calculations.

## 3.4 Mobile Edge Compute

Processing IoT data closer to the data source was first discussed in 2009 [68], using virtual machines to provide 'Cloudlets' close to a 'thin' or mobile client which has limited computing capabilities [4]. The evolution of Edge computing led to ETSI launching a Mobile Edge Compute (MEC) working group in 2015 [69] with a goal to *"...enable ultra-low-latency requirements as well as a rich computing environment for value-added services closer to end users.*" [70] MEC is a key component in the promise of high speed, low latency Massive IoT (MIOT) platforms described in 3GPP 5G Release 16 [71]. Baek, et al. [72] discuss 3GPP R16 and the use of mmWave [73] and MEC to provide ultra-reliable and low-latency communications (URLLC) and massive-input, massive-output (MIMO) capabilities, enabling sensor densities of up to one million sensors per square kilometer. This low latency, high-speed connectivity [74] is critical for the effective delivery of emerging technologies such as traffic management and collision avoidance systems in robotic and autonomous systems. Interlinked with the platform and communications, research into the real time processing of video streams has developed, and the emerging use of artificial intelligence (AI) for the extraction of information from streaming video. Xu, et al. [75] discuss the challenges of running AI-based video analytics on resource-constrained edge devices, such as CCTV cameras. Research into the use of deep learning algorithms [76] and federated analytics [77] are currently at the forefront of computing research. Deploying these models to the edge requires significant computing power [35]. Edge computing devices are evolving in terms of CPU, accelerators [58] and SmartNiC providing offload of networking functions [78], are enabling more complex workloads to run on edge compute platforms.

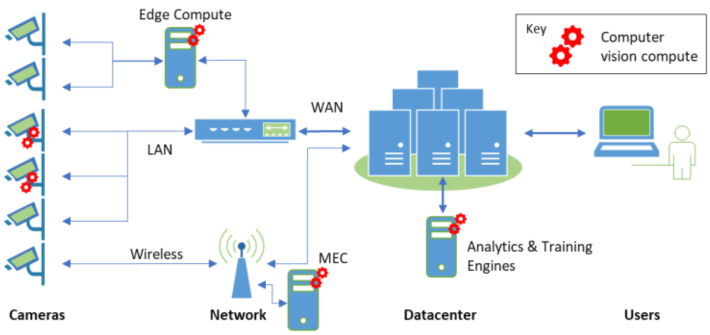



**Figure 3:** edge compute

Figure 3 above demonstrates the locations of the compute aspects of a surveillance system, including the on-camera, localized edge compute and MEC in 5G environments, but also the analytics backend platform, providing meta-analysis across the system, but also uses the combined datasets to train the algorithms for use at the edge, improving accuracy and ensuring that federated systems do not become fragmented, due to differing datasets flowing through the DNN.

# 4 Conclusions

The use of edge compute capabilities, combined with modern coding and management capabilities, can overcome challenges with network latency and enable real-time, preventative surveillance solutions for law enforcement. The reduction in compute cost and the emergence of lightweight neural network algorithms for computer vision can allow resource-constrained edge compute nodes to deliver an accurate analysis of streaming data in a timely manner.

The emergence of data-focused wireless technologies such as 5G, with mobile edge compute capabilities built into the core design of the networks to provide ultra-low latency analysis of the video data, will drive more analysis out of the central and cloud data centers. Moving these compute capabilities closer to the source of the data on edge devices will provide benefits to deliver surveillance solutions. The removal of latency due to network backhaul to cloud platforms will improve decision making processes locally in time-critical applications, such as autonomous vehicles. Emerging technologies provide the capability to analyze the video stream at the edge using autonomous decision making provided by neural network algorithms to decide when data should be transmitted. These capabilities can enable proactive interaction and intervention by users or for evidential purposes.

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