

Autonomous network traffic control system based on intelligent edge computing

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Abstract— This paper considers an intelligent network traffic control technology for high-reliability IoT services based on edge computing technology featuring modular micro-service computing technology, intelligent traffic analysis and predictive technologies for various applications. This paper proposes an autonomous network traffic control system that takes into account the recycling of edge technologies. Intelligent internet live monitoring service that provides online display of noise, vibration, gas readings, and field images on site as quickly as possible in the event of a civil complaint and efficiently store to prevent on-site images. This intelligent IoT edge computing technology proposes the structure, procedures, configuration and behaviour of intelligent IoT edge computing technologies, including IoT Things, data collection, data analytics capabilities, and gateways for delivering processed information to cloud servers. It applied smart construction monitoring as a representative service example.

Keywords— machine learning, data generator, deep learning, network machine learning, supervised learning

I. INTRODUCTION

Current resource-constrained IoT environment includes limited situations in which both the device itself and the networking environment are limited. To provide connectivity in this IoT environment, the existing Internet technology, TCP/IP or UDP/IP stack, supports networking and data transmission services. In addition, to assign IP addresses to a large number of IoT devices, IPv6 is being used instead of IPv4, and new HTTP layer is being developed to accommodate new wireless technologies such as LPWA, and connectivity layer between IPv6 and MAC [1].

In addition to increasing variety of IoT devices in the future, there is a need for scalability and effective networking and computing platform technologies to handle the myriad of data generated through these terminals. As a result, Edge/Fog computing technology is becoming popular to handle these technologies near users and IoT devices. In case of Edge computing, mobile edge computing (MEC) technology for mobile communication started, and the functions required for service are directly performed through the device and access rate and base station. However, most of them are used in parallel rather than in the technical differences between Edge computing and Fog computing, and in this paper they are accompanied by edge technology. With these various Edge/Fog computing technologies combined with a number of

IoT platforms developed for various existing IoT services, additional research and development activities that support inter-working and integration are under way [2-3].

As a specific example, many IoT services, such as smart city, smart factory, and smart healthcare, are being developed as separate IoT platforms, which have resulted in the ongoing confusion of many common IoT platforms. In particular, IoT devices have been developed to work with the gateway or actuator and have fixed shortcomings such as dedicated services along with specific company products, thus posing an obstacle to industrialization. There are activities to support integration of IoT platforms through international standardization, and platforms such as oneM2M and OCF's IoTivity are also being developed, but this is still not an integrated IoT platform [4-5].

In conclusion, the existing IoT platform cannot solve many IoT terminals, data processing, and supporting scalable connectivity through IP technology such as IPv6, CoAP, and central cloud server technology alone. Therefore, users and data such as edge computing technology are required to collect and process many data through a distributed structure and support effective connectivity and mobility in the secure environment and networking constraints of many IoT devices.

II. SYSTEM MODEL

This paper collects information from various sensors through intelligent edge computing equipment, analyzes the field situation through statistical and mechanical learning, and suggests the use of technology by choosing the quality of the network cameras that are illuminated.

This paper is characterized by installing IoT gateways without additional protocol stacks or applications installed in sensors, improving security compared to cloud-based IoT services, reducing server maintenance costs, and being linked to various cloud services.

Intelligent networking platform management and control over distributed Edge/Fog intelligent networking platforms based on information-centric networking-based edge intelligent networking platforms for scalability, mobility, and low latency for things and more.

This paper directly supports connectivity with thing through the thing networking section and supports scalability, real-time, and mobility in order to support connectivity of things in various forms and environments. Low-latency and

time-critical IoT services can be supported by mounting components for machine learning and hardening learning for intelligent processing of collected data [6].

This paper is comprised of information on intelligent IoE edge computing technologies for high-reliability IoT services and plans to apply smart IoT construction monitoring in particular.

Intelligent Edge Computing is an intelligent data processing equipment for edge analysis through its own artificial intelligence (AI) service and interlinked with big data analytics. To support edge analysis, IEC should increase data utilization through intelligent data processing, including data collection, dynamic storage, and real-time trust data pre-processing. In particular, the analytical model shall be updated periodically.

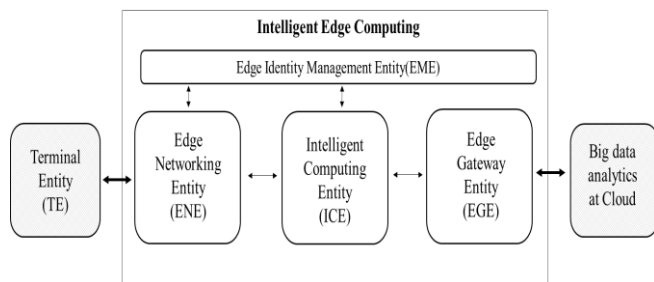


Figure 1. Intelligent Edge Computing Concept

Fig.1 describes intelligent IoT Edge computing configurations for high-trust IoT services. It consists of ENE, ICE, EGE and EME. Basically, intelligent edge computing can be placed in a location between computing devices such as smart phones and computers and terminal entities (TEs), including analysis of big data on the Internet and cloud computing, such as IoT (Internet of Things) devices.

- Edge Networking Entity (ENE): This entity provides connectivity to TEs that need to consider heterogeneous radio technology and resource constraints. Therefore, various radio technologies and protocols between TEs and IEC should be implemented.
- Intelligent Computing Entity (ICE): It provides edge analysis capabilities provided through AI services on its own or other analysis functions such as big data analysis of cloud computing. Data analysis function is performed through information collection. In addition to edge analysis, the TEs should be controlled through the analysis results.
- Edge Gateway Entity (EGE): The entity provides interworking capabilities for external institutions, including other IECs, and big data analytics capabilities through cloud computing can act like a gateway function.
- Edge Identity Management Entity (EME): The entity provides management functions that store ID types for all drawing elements, such as TE, ENE, ICE, and EGE, including data names as IDs. It also maps these IDs to metadata such as ICE switches and EGE locations.

Therefore, it can be included in mobility management such as TE's mobility.

As an example, it can be applied to the construction site. When noise, vibration and gas information are observed and the standard value is reached, high-quality image transmission service is available. As a security system, movement detection sensor, human body detection sensor, and high-quality image transmission is possible.

III. PROPOSED AUTONOMOUS TRAFFIC CONTROL SYSTEM

A. System concept & configuration

Fig.2 shows the system configuration of the autonomous traffic control system (ATCS) based on intelligent edge computing (IEC).

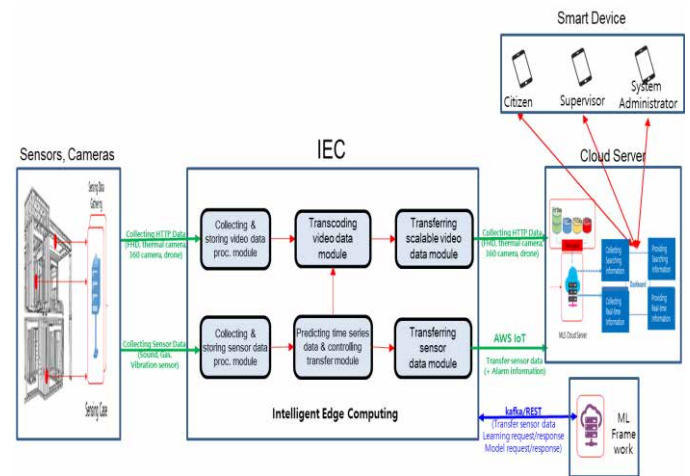


Figure 2. The system configuration of autonomous traffic control system based on intelligent edge computing

It is a network configuration that has intelligent edge computing and ML framework system in common structure, has sensing boxes in the West, and links to cloud services in the East. Civilians, on-site supervisors, and system administrators use services through the cloud. I/O interface processing (HTTP, AWS IoT, etc.), sensor or image data acquisition and storage processing (data acquisition and storage), Time Series data analysis and predictor (TS sensor data transmission) to improve recycling, it is possible to implement (rest API) using open source-based edge computing (such as EdgeX). Largely consists of sensing boxes, cameras, edge computing, and cloud servers. The sensing box is a collection of sensors that provide information on various sensors such as noise, vibration and gas to edge computing. The camera takes real-time images of construction sites at the FHD level and provides them to edge computing. Edge computing equipment includes not only the ability to provide IoE information processing, but also connectivity to provide data from the Things network, networking between the configuration nodes and components of each framework, and networking platforms with cloud servers that exist on the

Internet. The components of edge computing are sourcing data collection, static preset, ML-based prescriptions, video quality editing. Cloud servers receive sensor information through AWS IoT or video information through RTMP.

B. Total IoE edge computing procedure

The overall flow chart of this intelligent IoE edge computing technology is handled by raw data or single unit data from the sensor through the following procedure. Data received through the Seonsor is stored in the DB through the sensing data collection module. Data is also sent to the Statistical/ML preset module. The Statistical/ML preset module predicts data for the next cycle based on collected data. The predicted data is passed to the Decision module. Based on the algorithm, the Vision Module determines whether video data will be sent in high definition or low quality. The judgment results are transmitted to the Video Quality Attachment module. The Video Quality Attachment module sends video data to the cloud server based on the results of the spec module.

C. Prediction and decision method

There are two main types of DCS (Data transmission Control Scheme) as follows. SA-DCS is Static Alarm based Data transmission Control Scheme. DA-DCS is Dynamic Alarm based Data transmission Control Scheme. The prediction algorithm for decision is as follows. Static algorithm (SA-DCS) consists in Last Value (LV) and Moving Average (MA), etc. ML-based algorithm (DA-DCS) consists in Multi-Variable Regression Prediction (MVRP), Long Short Term Memory (LSTM), etc.

Parameters and operation methods are as follows.

- S : marginal noise (dB)
- C : Quality change sensitivity ($0 < C < 1$)
- Ns : Sampling per second
- Tw : Noise prediction window size (sec)
- Td : Quality reduction base time (sec)
- Uth : Network utilization limits (Kbps)
- FNth : False negative number limits (number)

In the Fig.3, the operational method of operating the operating algorithm first predicts the noise level over the next two seconds.

If $\text{Max}(S_i) > S * C$ and the network utilization is currently less than Uth, we change to high-quality for low-quality. For $\text{Max}(S_i) > S * C$, we record the last time that occurred. We Compare the difference between t (current time) and t' (last time). For $(t - t') > T_d$ case, we change the video from high-quality to low-quality. For example, $S=60$ dB, $C=0.8$, $Tw=30$ sec, and $T_d=10$ sec send video in high-quality for 10 seconds if it is expected to exceed 48 dB over the next 30 seconds.

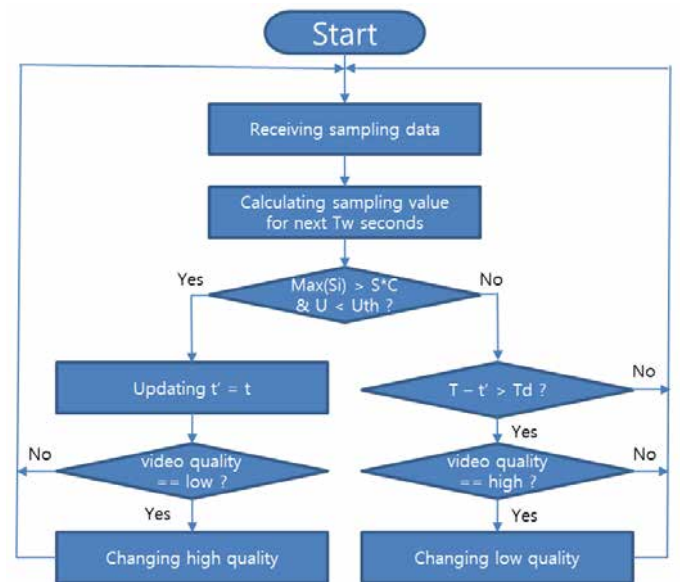


Figure 3. Prediction and decision method for proposed autonomous traffic control system

IV. SIMULATION RESULTS

In this chapter, we show the simulation results by implementing the prototype system. The software required for the system is as follows.

- Windows 10, (Ubuntu 16.04)
- Mysql 5.7.18
- Npcap 0.10 release 10
- Python 3.5.3
- Microsoft Visual C++ 2015 build tools
- Wireshark 2.4.1
- Tensorflow 1.8

For this simulation, the following performance indicators were used:

- Sample prediction error : Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE)
- Number of predicted failures : False negative (The number of samples in excess of S in the low-quality section), False positive (The number of samples not exceeding S in the high-quality section)
- High-quality transfer time ratio : Percentage of time transmitted in high-quality over time
- Network traffic usage : Measurements from the uplink interface of the Edge node
- Reduced LTE costs : Measure LTE cost reduction

We suppose the video bandwidth is based on youtube transfer rate:

- Low=500Kbps, High=3,000Kbps

We compare three schemes such as traditional scheme (TS), SA-DCS and DA-DCS. Especially, we will select the LV and

the MV_RP as a role of the representative algorithm of SA-DCS and DA-DCS, respectively.

As shown in Fig.4, the following compares the false negative numbers based on the network utilization limits for $S=69$ dB, $T_w=10$ sec, and $T_d=10$ sec. When using the same network usage limit, it is recommended to perform False negative performance in order of DA-DCS (MVRP) > SA-DCS (LV) > TS. False negative performance means the more accurate alarm is detected. DA-DCS is superior to SA-DCS because DA-DCS detect more accurate regression value.

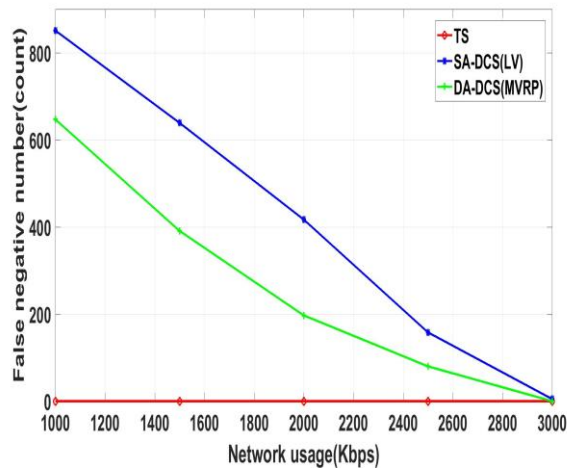


Figure 4. Performance evaluation : False negative number for proposed autonomous traffic control system

The network traffic usage is compared based on the number of false negatives for $S=69$ dB, $T_w=10$ sec, and $T_d=10$ sec. The network traffic usage performance is good in the order of DA-DCS(MVRP) > SA-DCS(LV) > TS when the same false negative number is. The network traffic usage performance means the traffic usage cost is reduced. DA-DCS is superior to SA-DCS because DA-DCS use lower network traffic.

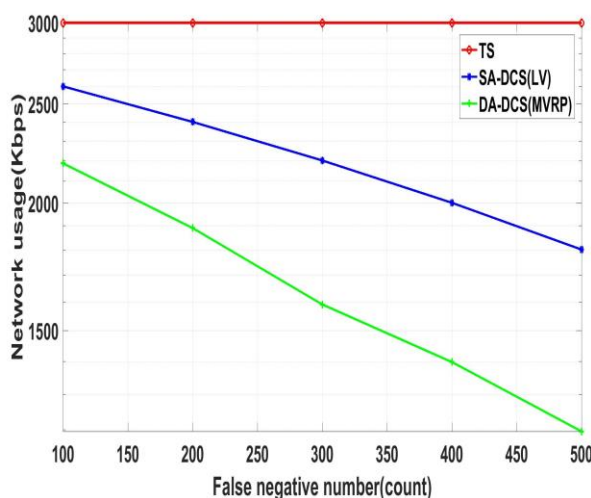


Figure 5. Performance evaluation : Network traffic usage for proposed autonomous traffic control system

V. CONCLUSIONS

This paper can provide monitoring services using real-time media and data collaboration services for smart construction. While services using the Internet of Things are currently being introduced competitively by many companies, there are still many areas that need to be developed as public services. This technology will provide an opportunity to transform past passive monitoring methods into active or instantaneous collaborative services. In addition, the collected data can be used as basic data such as machine running. This paper includes video traffic control policies to reduce costs and traffic shaping control technology for high reliability.

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intelligent service.

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