Intelligent Fabric Enabled 6G Semantic Communication System for In-Cabin Scenarios

Yuan Tang, Ning Zhou, Qiao Yu, Di Wu, *Senior Member, IEEE*, Chong Hou, Guangming Tao, and Min Chen, *Fellow, IEEE*

***Abstract*— With the large-scale commercialization of 5G, the global industry has started the exploration of the next generation mobile communication technology (6G). From mobile Internet, to IoT, and then to the smart connection of everything, 6G will transform from 5G's service objects of people and things to the intelligent networking of agent that supports human–machine–object. 6G networks should have the characteristics of ubiquitous intelligence and ubiquitous perception, which poses challenges for 6G network construction. Therefore, we propose a 6G Semantic Communication Scheme based on Intelligent Fabrics for transportation in-cabin scenarios (6GSCS-IF), which can provide senseless intelligent interaction in transportation in-cabin environment through widely and flexibly deployed intelligent fabrics, demonstrating the superiority of intelligent fabrics in realizing human–machine–object intelligent sensory interaction. Then, we propose a Deep Learning-based Semantic Communication Model for Time-series data (DL-SCMT), and use deep learning for semantic sensing and information extraction to build an end-to-end semantic communication system. The experimental results show that the semantic communication services provided by this model can achieve better signal reconstruction and higher-order intelligent services compared with traditional communication methods.**

***Index Terms*— Semantic communication, intelligent fabric, 6G, deep learning.**

I. Introduction

In recent years, technology in the field of mobile communication has developed rapidly, and the evolution from 1G to 5G has seen a disruptive iteration of mobile communication technology occur every decade [1]. Currently, relying on the large-scale deployment of 5G commercialization, real-time mobile communication has been empowered to smart cities, autonomous driving, cloud medical consultation and other fields. However, with the development of cloud-native, artificial intelligence, big data, information fusion and other information technologies, global mobile business data traffic is exploding and is expected to far exceed the current communication service threshold of 5G in 2030 [2], [3]. Moreover, the intelligence, energy saving and greening of communication technologies are already the trend of social development. All these will become 5G mobile communication bottlenecks. Therefore, the next generation of mobile communication (6G) should make some changes in response to these challenges.

The future sixth generation (6G) mobile communication system will be compatible with 5G in the human–machine–object interconnection of all things, pioneering the intelligent connection of all things [2], [4]. 6G will integrate artificial intelligence, big data, blockchain and other technologies to realize the coupling of communication, perception, computing and network, finally completing the interconnection of intelligent bodies and digital twin, and achieving intelligent ubiquity and perception [5]–[8]. Under 6G communications, smart bodies will make the leap to intelligent connectivity, continuously improving the quality of people's lives and promoting high-quality development of social production methods through intelligent interconnection and collaborative symbiosis of people, machines and things. The 6G network will meet the performance requirements of full area coverage, high density, high reliability, low latency, high spectral efficiency, large connectivity and intelligent communication [9], [10]. In particular, 6G's "full domain coverage" encompasses two different communication domains, extending outwards to the air-space integration, and deepening inwards to new human-computer interaction, i.e. providing new applications such as future immersive cloud XR, holographic communication, sensory interconnection, digital twin and metaverse. Therefore,

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Yuan Tang and Qiao Yu are with the School of Computer Science and Technology, Huazhong University of Science and Technology, Wuhan 430074, China (e-mail: yuan_tang@hust.edu.cn; qiaoyu_epic@hust.edu.cn).

Ning Zhou is with the Tongji Medical College, Huazhong University of Science and Technology, Wuhan, Hubei 430074, China (e-mail: zhouning@tjh.tjmu.edu.cn).

Di Wu is with the School of Computer Science and Engineering, Sun Yat-sen University, Guangzhou 510006, China, and also with the Guangdong Key Laboratory of Big Data Analysis and Processing, Guangzhou 510006, China (e-mail: wudi27@mail.sysu.edu.cn).

Chong Hou is with the Sport and Health Initiative, Optical Valley Laboratory, the Wuhan National Laboratory for Optoelectronics, and the School of Optics and Electronic Information, Huazhong University of Science and Technology, Wuhan, Hubei 430074, China (e-mail: chong@hust.edu.cn).

Guangming Tao is with the Sport and Health Initiative, Optical Valley Laboratory, the Wuhan National Laboratory for Optoelectronics, and the State Key Laboratory of Material Processing and Die & Mould Technology, School of Materials Science and Engineering, Huazhong University of Science and Technology, Wuhan, Hubei 430074, China (e-mail: tao@hust.edu.cn).

Min Chen is with the School of Computer Science and Technology, Huazhong University of Science and Technology, Wuhan, Hubei 430074, China, and also with the Sport and Health Initiative, Optical Valley Laboratory and the Wuhan National Laboratory for Optoelectronics, Hubei 430074, China (e-mail: minchen2012@hust.edu.cn).

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6G should have the ability to sense individual states and environmental contextual semantics in human-computer interaction, while meeting the characteristics of senseless ubiquity and intelligent interactivity.

6G communication technology has been studied by a number of scholars from various perspectives, of which semantic communication is an intelligent communication method that focuses on data semantics and transmits the core content of the batch information flow, which fits the intelligent interaction characteristics of intelligent bodies and meets the development needs of 6G [11]. Weng *et al.* [12] designed a semantic communication system for speech signals in semantic communication systems. Xie *et al.* [13] proposed a text-oriented semantic communication system. The above semantic communication system studies ignore the core features of intelligent perception, perceptual ubiquity and intelligent interactivity of 6G communication. It will be very meaningful and challenging to design a relying carrier for intelligent perception, interaction and computation in one under 6G communication, and to realize semantic communication with application scenarios.

Flexible fabric materials are developing rapidly and are widely used in medical and health, sports and fitness, and living scenarios [14]–[16] with rich and unique use interaction experience and scientific research value. Su *et al.* [17] developed a muscle fiber-excited piezoelectric nonwoven fabric with adjustable mechanical properties for wearable physiological monitoring. Michael and Howard [18] used the fabric to sense athletes' body movements and learn motor postures. Fabrics support bending and stretching in use due to their material properties and possess unbreakable characteristics. With these advantages, intelligent fabrics, which combine artificial intelligence and electrical properties, can be an important medium for individual interaction and perception. Intelligent fabrics are low-cost, can be deployed on a large scale and are energy-efficient and support long-life operation. Compared to traditional collection devices, intelligent fabrics embedded with algorithms can filter and extract value from data, enabling semantic extraction for individual states and environmental contexts. Therefore, the properties of intelligent fabrics are in line with the intelligent and senseless interaction and intelligent ubiquitous characteristics of 6G communication, and have the potential for semantic communication. As 6G communication deepens internally, intelligent fabrics can be used as a carrier and solution for new human-computer interaction.

In this paper, considering the characteristic vision of 6G communication technology in intelligent sensing, environmental contextual semantic awareness and intelligent ubiquity, we propose a 6G semantic communication scheme for in-cabin scenarios of transportation in combination with intelligent fabrics, and analyse in detail the components and functions of the semantic communication system enabled by intelligent fabrics; meanwhile, a deep learning-based semantic communication model is designed for temporal data. The main contributions of this thesis are the following:

1) We propose a 6G semantic communication scheme based on intelligent fabrics for transportation in-cabin scenarios. The scheme is oriented to transportation scenarios, such as airplanes, trains, where users perform intelligent senseless interactions in an environment where intelligent fabrics are widely deployed, the intelligent fabrics cognize user behavior and environmental context, complete semantic extraction, and then combine with 6G communication network of the air-space-ground integrated to obtain higher-order intelligent services. At the same time, we introduce in detail the process and service types of semantic communication in the intelligent fabric scenarios from the communication data processing level.
2) We propose a deep learning-based semantic communication model for time-series data. The model supports semantic communication of time-series data under different signal-noise physical channels, chieve high quality signal data reconstruction, and provides higher-order deep learning services.
3) We carry out experiments to simulate communication environments with different signal-to-noise ratios on real data, and verify the function of the proposed semantic communication model. Compared with traditional communication methods, DL-SCMT has superior performance in various performance indicators.

The remainder of this paper is organized as follows. First, the 6GSCS-IF is described (Section II). Then, this is followed by the description of DL-SCMT (Section III). Section IV describes our experimental setup, presents the experimental results and analyzes them. Section V concludes this paper.

II. 6GSCS-IF

6GSCS-IF combines the widely deployed intelligent fabrics with 6G semantic communication, which can realize intelligent and senseless interaction in multiple transportation in-cabin scenarios, reflecting the advantages of 6G communication in intelligent ubiquitous and intelligent interaction, and providing a new solution idea for semantic communication. In the following, we will introduce 6GSCS-IF in detail from scene communication level and data processing level respectively.

A. Scene Communication Level of 6GSCS-IF

6GSCS-IF consists of four parts: intelligent fabric environment, intelligent fabric semantic sensing terminal, semantic transmission channel, and remote artificial intelligence platform, which connects from environmental information collection, environmental contextual semantic sensing, semantic information physical channel transmission to semantic information deep learning service, as shown in Fig 1. The intelligent fabric's intelligent ubiquity and intelligent perception are fully empowered into the communication network, breaking the physical and digital barriers, integrating individuals into the cyberspace, realizing the intelligent interconnection of human–machine–object, and providing new ideas for 6G network semantic communication.

Intelligent fabric environment aims to collect raw data in the fabric space. Intelligent fabric uses electromagnetic, capacitive, resistive and other basic signals to sense the state changes of the scene individual and the environment, with its

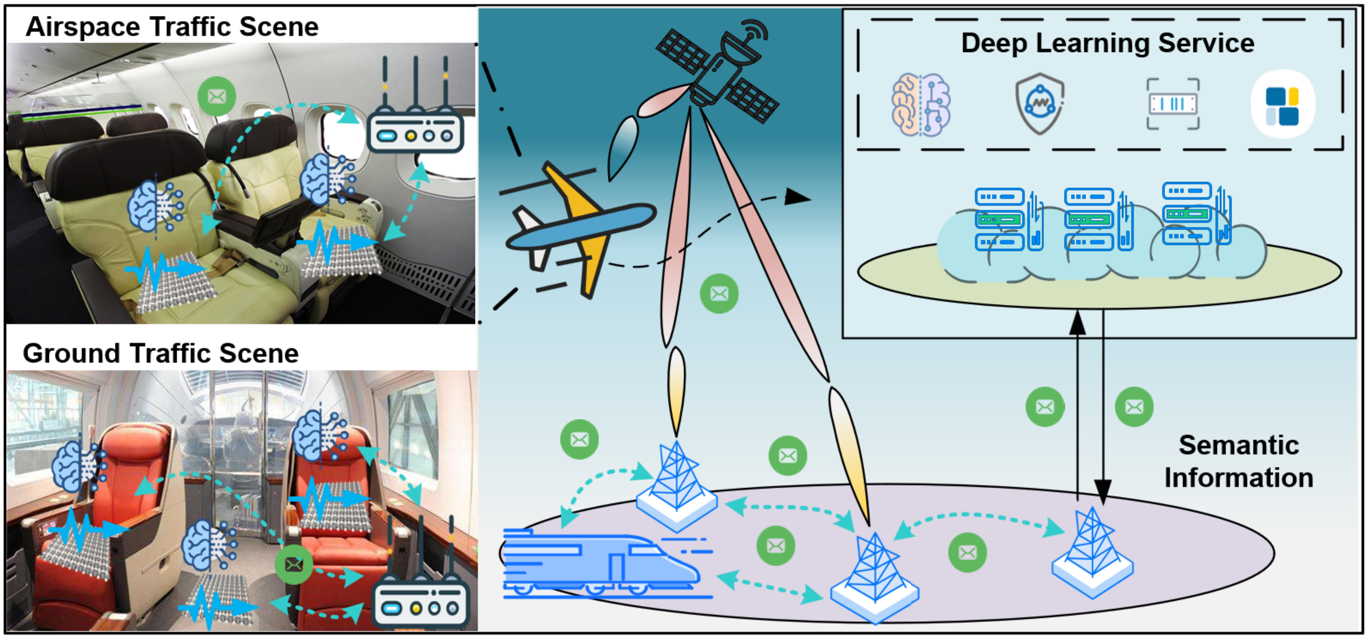

Fig. 1. The scene communication of 6GSCS-IF.

low-cost non-sensitive characteristics, support a wide range of deployment, from multiple angles and multi-dimensional three-dimensional perception of spatial conditions. Intelligent fabric can be embedded into the carpet, cushion, table, wall, etc. to form a fabric space, so that the individual becomes part of the environment, every move can be captured by the intelligent fabric. As the intelligent fabric has green low power consumption, it can interact actively for a long time and perceive the environment in all aspects.

The intelligent fabric semantic cognition terminal block is intended to refine the information perceived by the fabric. The semantic cognition function designs a matching deep network according to the characteristics of the data flow, extracts the perceived environmental data in real time, improves the granularity of data value, reduces the amount of communication transmission data, and can also better provide timely services for downstream delay-sensitive tasks.

The semantic information physical channel transmission block architecture supports scene information transmission and realizes end-to-end semantic information flow transmission. The transmission of semantics at the physical communication level involves air-space-ground joint communication, with data aggregated from the flight vehicle end to the satellite in the airspace, and then connected to the base station cluster at the ground end to complete high-speed air-to-ground data transmission, and the ground base station cluster distributes the semantics to the target cloud server according to the optimal routing algorithm to provide continuous timing information for subsequent semantic metadata processing.

The remote AI platform module can complete semantic recovery and higher-order deep learning services for semantic metadata. The semantic data reaching the intelligent platform end of the cloud service can be restored according to

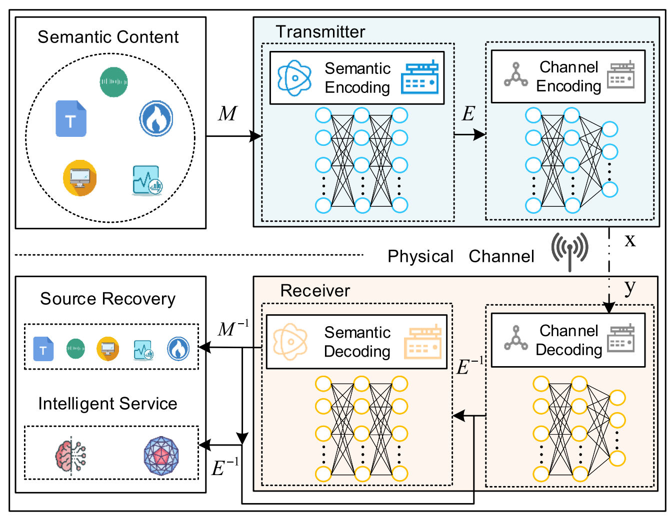

Fig. 2. The data processing of 6GSCS-IF.

information categories and scales to achieve end-to-end communication of environmental semantic information; semantic metadata can also be used as high-dimensional features of information and directly input into deep learning models to continue to carry out state sensing and intelligent services for the environment or human body.

B. Data Processing Layer of 6GSCS-IF

Semantic communication data processing consists of four parts: semantic information source, semantic information transmitter, semantic information receiver, and semantic information higher-order sensing end, as shown in Fig 2. The semantic information source is derived from the intelligent fabric environment and contains basic data types such as textual information, radio wave signal information and digital scalar information. The semantic information transmitter encodes the semantic information source into a physical channel signal. The semantic information receiver reconstructs the physical channel signal into the original signal. The semantic information higher-order sensing end then reconstructs the sensory state based on the restored signal; it can also perform higher-order deep intelligence services based on the semantic source code output from the channel decoder. In the following we will describe the semantic information transmitter and semantic information receiver in detail.

1) Transmitter: The semantic transmitter consists of a semantic coder and a channel coder to realize the extraction of semantic features of the source message. The semantic coder accepts the perceptual multivariate information from the intelligent fabric space, unlike the traditional compression methods that reduce the amount of data in bytes and unrecorded semantics of the message; the semantic coder can refine the expression features of the message in high dimensions, which is the compression and recoding of the semantics of the message. The channel coder accepts the semantic source code information output from the semantic coder and converts the semantic information into channel code, while achieving compression of data volume in the data dimension. The specific process is as

$$X = C_{En}\left(S_{En}(M)\right), \tag{1}$$

where $M = [m_1, m_2, \cdots, m_L]$ is the time-series information perceived by the intelligent fabric, L denotes the length of the time-series sequence; $S_{\mathrm{En}}(\cdot)$ is the semantic coder, we use multiple 1D-ResNets to extract semantic source code; $C_{En}(\cdot)$ denotes the channel coder, we use a two-layer fully connected neural network which decreasing number of neurons, to achieve data compression and obtain the channel code (X).

The channel code (X) is input into the physical channel for transmission to the receiver side. The physical channel is an overview of the physical communication link, where data from the user's end may pass through routers, various base stations, and even satellites, etc. The data transmitted will no longer be the raw symbolic encoded data of the past, but will be semantic information with a high degree of privacy protection and full value of information granularity. The physical channel will also introduce some interference signals, resulting in noisy semantic channel codes. The process is as

$$Y = T_c(X), \tag{2}$$

where $X = [x_1, x_2, \cdots, x_N]$ is the channel code, $T_c(\cdot)$ denotes the physical channel, different physical channels will introduce different distributions of noise; Y is the channel code transmitted to the receiver.

2) Receiver: The receiver consists of a channel decoder and a semantic decoder to decode the semantic channel code and restore the original information. The channel decoder accepts the semantic channel code (Y) containing noise and outputs the semantic source code; the semantic source code can be used by the higher-order services of deep learning, and can

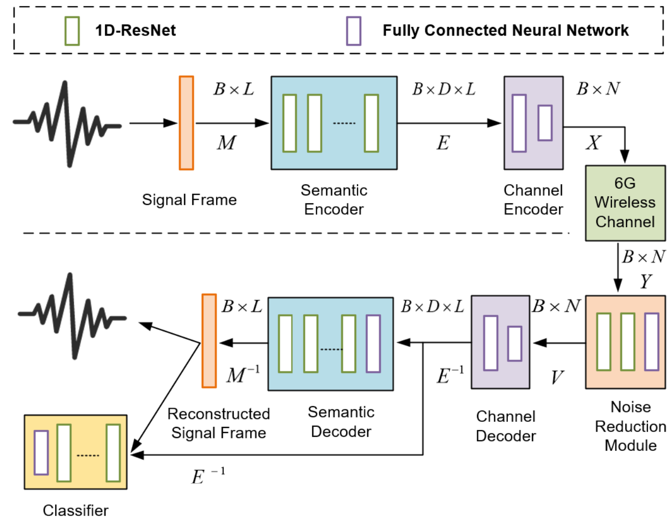

Fig. 3. The network structure of DL-SCMT.

also be input to the semantic decoder for original information restoration. The process is as

$$M^{-1} = C_{De}\left(S_{De}(Y)\right), \tag{3}$$

where $Y = [y_1, y_2, \cdots, y_N]$ is the channel code from the physical channel with certain noise; $C_{De}(\cdot)$ denotes the channel decoder, which decompresses the channel code using two fully-connected layers with increasing neuron count; $S_{De}(\cdot)$ is the semantic decoder, which recovers the semantic code into the input signal of the intelligent fabric for other subsequent services; and M^{-1} is the recovered timing information.

III. DL-SCMT

To address the needs of 6GSCS-IF in semantic communication of intelligent fabrics, we propose a deep learning-based semantic communication model for time-series data. The aim is to achieve semantic communication of time-series information. The model consists of three modules: the autoEncoder (AE) semantic communication network, the noise reduction network, and the classification network, as shown in Fig 3. The three modules are trained in batches, with the AE semantic communication network trained first; then the model is added with noise and used as the training environment for the noise reduction network; the classification network can be trained in both noisy and noiseless environments using the previous pre-trained model.

The AE semantic communication network completes the basic data semantic encoding to semantic decoding process and enables semantic communication of timing signals under a noise-free physical channel. The noise reduction network is connected behind the physical channel to remove the noisy signals in the physical channel transmission. Then, we design two classification networks, one can input the semantic source code and the other can input the restored original data.

A. Model Description

1) AE Semantic Communication Network: The AE semantic communication network, as the base model of semantic communication under the ideal physical channel, covers all processes of the 6GSCS-IF data processing process and enables semantic communication of intelligent fabric timing data. The AE semantic communication network is divided into encoder and decoder parts by the physical channel, which distills the data from the original information into the physical channel code, and then reverses the processing to restore the original data.

The encoder module consists of the semantic encoding network and the channel encoding network. The semantic encoding network consists of multiple semantic ResNet modules that receive $M \in \Re^{B\times L}$ and output the semantic code ($E \in \Re^{B\times D\times L}$). The semantic ResNet module invokes the ResNet [19] idea of feeding variables into a one-dimensional convolutional network and self-summing them to achieve refining new information without losing the data features of the original variables. The channel coding network is a two-layer fully connected neural network, with input variables $E \in \Re^{B\times D\times L}$ and output $X \in \Re^{B\times N}$. The variable $X \in \Re^{B\times N}$ enters the physical channel for transmission to the receiver.

The decoder module contains the channel decoding network and the semantic decoding network, and the process is inverse to that of the encoder module. The channel decoder network inputs the variable $Y \in \Re^{B\times N}$ and outputs the semantic code ($E^{-1} \in \Re^{B\times D\times L}$). The semantic decoding network input $E^{-1} \in \Re^{B\times D\times L}$, is recovered to $M^{-1} \in \Re^{B\times L}$, where the semantic ResNet is also used.

2) Noise Reduction Network and Classification Network: The noise reduction network input from the physical channel $Y \in \Re^{B\times N}$, $Y \in \Re^{B\times N}$ may contain noise introduced in the communication transmission, and the noise reduction network output after the noise reduction $V \in \Re^{B\times N}$.

The classification network is used as a sample of higher-order services for semantic communication, and the feasibility of semantic communication services is demonstrated in a fundamental way. Subsequent deep-learning higher-order services based on semantic communication can cover a wider and richer range of application scenarios. The classification network can discriminate the signal type based on the semantic source code; it can also input the final recovered $M^{-1} \in \Re^{B\times L}$ and then output the signal classification.

B. Loss Design

The AE semantic communication network is trained to converge with the input variable $M \in \Re^{B\times L}$ and the output $M^{-1} \in \Re^{B\times L}$. Since the input variable is a time-series signal, we choose the cosine similarity to define the distance of the time-series variable. The specific loss is calculated as

$$EDLoss\left(M,\ M^{-1}\right) = 1 - \cos\left(M,\ M^{-1}\right), \tag{4}$$

where $cos(\cdot)$ calculates the cosine of the angle between the two input vectors.

The goal in the training of the noise reduction network is to convert the noisy $Y \in \Re^{B\times N}$ into clean $V \in \Re^{B\times N}$, i.e., to make the output physical channel variables consistent with the channel codes output by the encoder module. In the debugging process, we found that the recovered original information would fluctuate significantly by just constraining the intermediate variables to be consistent, so we restore the $V \in \Re^{B\times N}$ output from the noise reduction network to the original information $M^{-1} \in \Re^{B\times L}$ and then follow the corresponding input $M \in \Re^{B\times L}$. $M \in \Re^{B\times L}$ to compare the similarity, which enables the recovered timing signal to be closer to the original timing signal with less fluctuations. Then, in order to allow the noise reduction module to output high-quality $V \in \Re^{B\times N}$ even when processing noiseless signals, this part of the requirement is also taken into account in the training in this paper. The specific loss is calculated as

$$\begin{aligned} &deNoiseLoss\left(X,\ V,\ M,\ M^{-1}\right) \\ &\quad = EDLoss\left(X,\ V_{deNoise}\right) + EDLoss\left(M,\ M^{-1}_{deNoise}\right) \\ &\qquad + EDLoss\left(X,\ V_{noNoise}\right) + EDLoss\left(M,\ M^{-1}_{noNoise}\right), \end{aligned} \tag{5}$$

where $V_{deNoise}$ is the output of the noisy Y processed by the noise reduction module; $M^{-1}_{deNoise}$ denotes the timing signal of the AE semantic communication model according to the output of $V_{deNoise}$. Similarly, $V_{noNoise}$ and $M^{-1}_{noNoise}$ represent the corresponding data in the physical channel training environment without noise, respectively.

The training goal of classification network is to be able to distinguish various types of time-series signals, but it is too ideal to classify only clean signals, which cannot meet the robustness requirements of classifiers in practical scenarios. Therefore, in this paper, we need to classify signals with no noise, signals reconstructed with semantic communication under target SNR value noise, and signals reconstructed with semantic communication under small SNR value noise. The specific loss is calculated as

$$\begin{aligned} &ClassificationLoss(clear\_signal,\ targetSNR\_signal, \\ &\quad smallNoise\_signal,\ label) \\ &= CrossEntropyLoss(clear\_signal,\ label) \\ &\quad + CrossEntropyLoss(targetSNR\_signal,\ label) \\ &\quad + CrossEntropyLoss(smallNoise\_signal,\ label), \end{aligned} \tag{6}$$

where $CrossEntropyLoss(\cdot)$ is the cross-entropy loss function; label denotes the signal class.

C. Model Training and Testing

The semantic communication model designed in this paper involves 3 networks, and the networks are trained sequentially. The AE semantic communication network is trained first, then the noise reduction network is trained, and finally the classification network is trained. Each of the networks trained first will be the training environment for the later networks, and the classification network trained in this paper takes the time-series signals as input.

1) Training Stage: The training process of the AE semantic communication network is shown in algorithm 1. In one iteration cycle, the AE semantic communication network receives the timing data M sensed by the intelligent fabric, and gets E from the semantic coder, the channel coder processes E to get X, then the channel decoder gets the semantic code E^{-1} according to X, then the semantic decoder restores E^{-1} to timing information, and finally calculates the loss according to M and M^{-1} to calculate the loss and update the network.

The noise reduction network training process is shown in algorithm 2. The AE semantic communication network parameters are fixed and do not participate in parameter updates. In one iteration, the encoder module of the AE network is used to output X, and then the noise reduction network is passed under the noisy and noiseless physical channels, respectively, to finally output $M_{deNoise}^{-1}$ and $M_{noNoise}^{-1}$. Then, the loss is calculated using the formula 5 to calculate the loss, and finally update the noise reduction network parameters.

The classification network training process is shown in algorithm 3. First, the parameters of the AE network and the noise reduction network are fixed and not involved in the training. Then the first reconstructed signal is obtained from the direct input to the decoder module, followed by adding noise with SNR value and less noise to make the data flow into the DL-SCMT model to output the recovered time-series signal $M_{goalSNR}^{-1}$ and $M_{smallSNR}^{-1}$, and then calculate the loss according to the formula 6, and finally update the classification network parameters.

Algorithm 1: Training Algorithm of the AE Semantic Communication Network in the Proposed DL-SCMT

Input: Time-series signal data sensed by intelligent fabrics.

Initialize data loader;
Initialize training parameters;
for *epoch* **do**
    // Encoder.
    $S_{En}(M) \rightarrow E$;
    $C_{En}(E) \rightarrow X$;
    // Decoder.
    $C_{De}(X) \rightarrow E^{-1}$;
    $S_{De}\left(E^{-1}\right) \rightarrow M^{-1}$;
    // Calculate loss.
    $loss = EDLoss\left(M,\ M^{-1}\right)$, by using Eq.4;
    Update θ_{AE} with BGD;
end
Save the encoder model of the AE network and the decoder model of the AE network;

Output: AE Semantic communication model.

2) Test Stage: In the testing phase, the AE semantic communication model and the classification network that join the noise reduction network need to be tested. A variety of channel models can be used for the physical channel, and AWGN channel is used in this paper. With different channel model requirements, the noise reduction physics can be retrained without training the AE semantic communication model. This also reflects the compatibility of the DL-SCMT model we designed with various physical channel models.

Algorithm 2: Training Algorithm of the Noise Reduction Network in the Proposed DL-SCMT

Input: Time-series signal data sensed by intelligent fabrics, physical channel noise function, fixed SNR value.

Initialize data loader;
Initialize training parameters;
Load the encoder model of the AE network;
Load the decoder model of the AE network;
for *epoch* **do**
    // Encoder.
    $S_{En}(M) \rightarrow E$;
    $C_{En}(E) \rightarrow X$;
    // Processing in the case of a noisy signal.
    $AddNoise(X,\ SNR) \rightarrow Y_{deNoise}$;
    $deNoise\left(Y_{deNoise}\right) \rightarrow V_{deNoise}$;
    $C_{De}\left(V_{deNoise}\right) \rightarrow E_{deNoise}^{-1}$;
    $S_{De}\left(E_{deNoise}^{-1}\right) \rightarrow M_{deNoise}^{-1}$;
    $loss_{deNoise} = EDLoss\left(X,\ V_{deNoise}\right) + EDLoss\left(M,\ M_{deNoise}^{-1}\right)$, by using Eq.4;
    // Processing without noise signal.
    $deNoise\left(X\right) \rightarrow V_{noNoise}$;
    $C_{De}\left(V_{noNoise}\right) \rightarrow E_{noNoise}^{-1}$;
    $S_{De}\left(E_{noNoise}^{-1}\right) \rightarrow M_{noNoise}^{-1}$;
    $loss_{noNoise} = EDLoss\left(X,\ V_{noNoise}\right) + EDLoss\left(M,\ M_{noNoise}^{-1}\right)$, by using Eq.4;
    // Calculate the total loss.
    $loss = loss_{deNoise} + loss_{noNoise}$, by using Eq.5;
    Update $\theta_{deNoise}$ with BGD;
end
Save the noise reduction network model;

Output: Noise reduction network model.

D. Performance Metrics

The core point of semantic communication is the extraction and reconstruction of information from the signal. The introduction of noise in the physical channel causes the reconstructed signal to deviate from the source signal, and the use of metrics to scientifically characterise the differences between signals helps in the optimisation and comparison of models. In this paper, the metrics used are cosine similarity, MSELoss, Source to Distortion Ratio (SDR) [20], and Log Spectral Distance (LSD). Among them, the metric of cosine similarity is the same as Eq. 4.

MSELoss measures the mean square error of the input and output variables, and a smaller value indicates a better reconstruction. The calculation formula is as

$$MSELoss = \frac{\sum_{i=0}^{n}\left(m_i - m_i^{-1}\right)^2}{n}, \tag{7}$$

SDR calculates the power of the difference between the input signal and the reconstructed signal as the denominator, and then uses the power of the input signal as the numerator. It can reflect the influence of reconstruction error on the

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Algorithm 3: Training Algorithm of the Classification Network in the Proposed DL-SCMT

Input: Time-series signal data sensed by intelligent fabrics, physical channel noise function, fixed SNR value.

Initialize data loader;
Initialize training parameters;
Load the encoder model of the AE network;
Load the decoder model of the AE network;
Load the noise reduction network model;
for *epoch* **do**
  $C_{En}\left(S_{En}(M)\right) \rightarrow X$;
  // Processing without noise signal.
  $S_{En}\left(C_{En}(X)\right) \rightarrow M_{\text{clear}}^{-1}$;
  $Classification(M_{\text{clear}}^{-1}) \rightarrow pridict_{clear}$;
  $loss_{clear} = CrossEntropyLoss(pridict_{clear},\ label)$;
  // Processing when SNR is the target value.
  $addNoise(X,\ SNR) \rightarrow Y_{goalSNR}$;
  $deNoise(Y_{goalSNR}) \rightarrow V_{goalSNR}$;
  $S_{En}\left(C_{En}\left(V_{goalSNR}\right)\right) \rightarrow M_{goalSNR}^{-1}$;
  $Classification\left(M_{\ goalSNR}^{\ -1}\right) \rightarrow pridict_{goalSNR}$;
  $loss_{goalSNR} = CrossEntropyLoss(pridict_{goalSNR},\ label)$;
  // Processing of signals with a small amount of noise.
  $addNoise(X,\ smallSNR) \rightarrow Y_{smallSNR}$;
  $deNoise(Y_{smallSNR}) \rightarrow V_{smallSNR}$;
  $S_{En}\left(C_{En}\left(V_{smallSNR}\right)\right) \rightarrow M_{smallSNR}^{-1}$;
  $Classification(M_{smallSNR}^{-1}) \rightarrow pridict_{smallSNR}$;
  $\text{loss}_{smallSNR} = CrossEntropyLoss(pridict_{smallSNR},\ label)$;
  // Calculate the total loss.
  $loss = loss_{clear} + loss_{goalSNR} + loss_{smallSNR}$, by using Eq.6;
  Update $\theta_{Classification}$ with BGD;
end
Save the classification network model;

Output: Classification network model.

original signal. The larger the value, the better the signal reconstruction effect, and the smaller the MSELoss. The calculation is as

$$SDR = 10\log_{10}\frac{\|M\|^2}{\left\|M - M^{-1}\right\|^2}, \tag{8}$$

LSD is the distance measure between two spectra, and the smaller the value, the closer the two signals are, the better the reconstruction effect. The calculation formula is

$$LSD = \sqrt{\frac{1}{2\pi}\int_{-\pi}^{\pi}\left[10 * \log_{10}\frac{P(stft(M))}{P(stft(M^{-1}))}\right]^2 dw}, \tag{9}$$

where $stft(\cdot)$ denotes the short-time Fourier transform function and $P(\cdot)$ is the spectral power function.

In addition to comparing the semantic communication quality of service in terms of signal reconstruction effects, we also take into account the downstream higher-order deep learning. In this paper, a classifier is attached to the signal reconstruction module to distinguish different signal types sensed by the intelligent fabric. The accuracy of the classification is indicative of the enhanced effect of semantic communication in real service applications. The calculation formula is as

$$Accuracy = \frac{\sum_i^n \text{Equal(predict, label)}}{n} \times 100\%, \tag{10}$$

where n is the amount of data; $predict$ and $label$ denote the output category and the actual data category of the

TABLE I
PARAMETERS OF TRADITIONAL COMMUNICATION BASELINES

	8-Bit+RS	8-Bit+Turbo
Frame length	100	100
Source coding	8-Bit encoding	8-Bit encoding
Channel coding	RS(255, 225) coding	Turbo(R=1/3) coding
Modulation	64-QAM	64-QAM

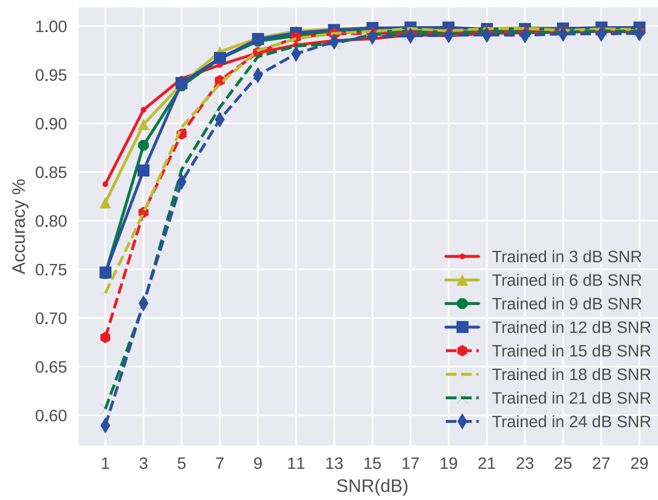


Fig. 4. Classification accuracy of models trained under noisy physical channels with different SNR values.

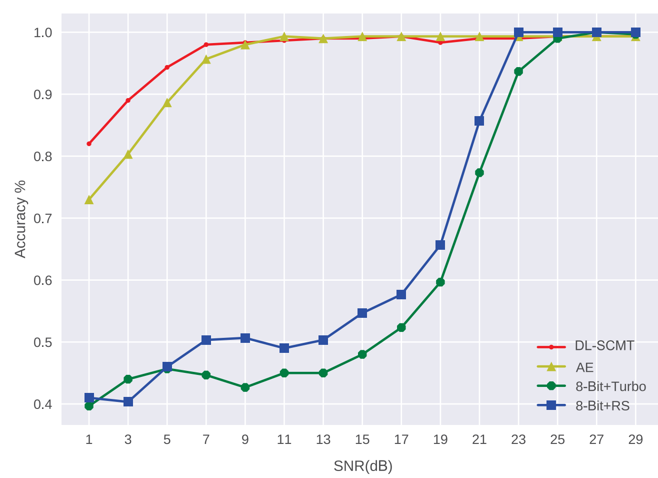
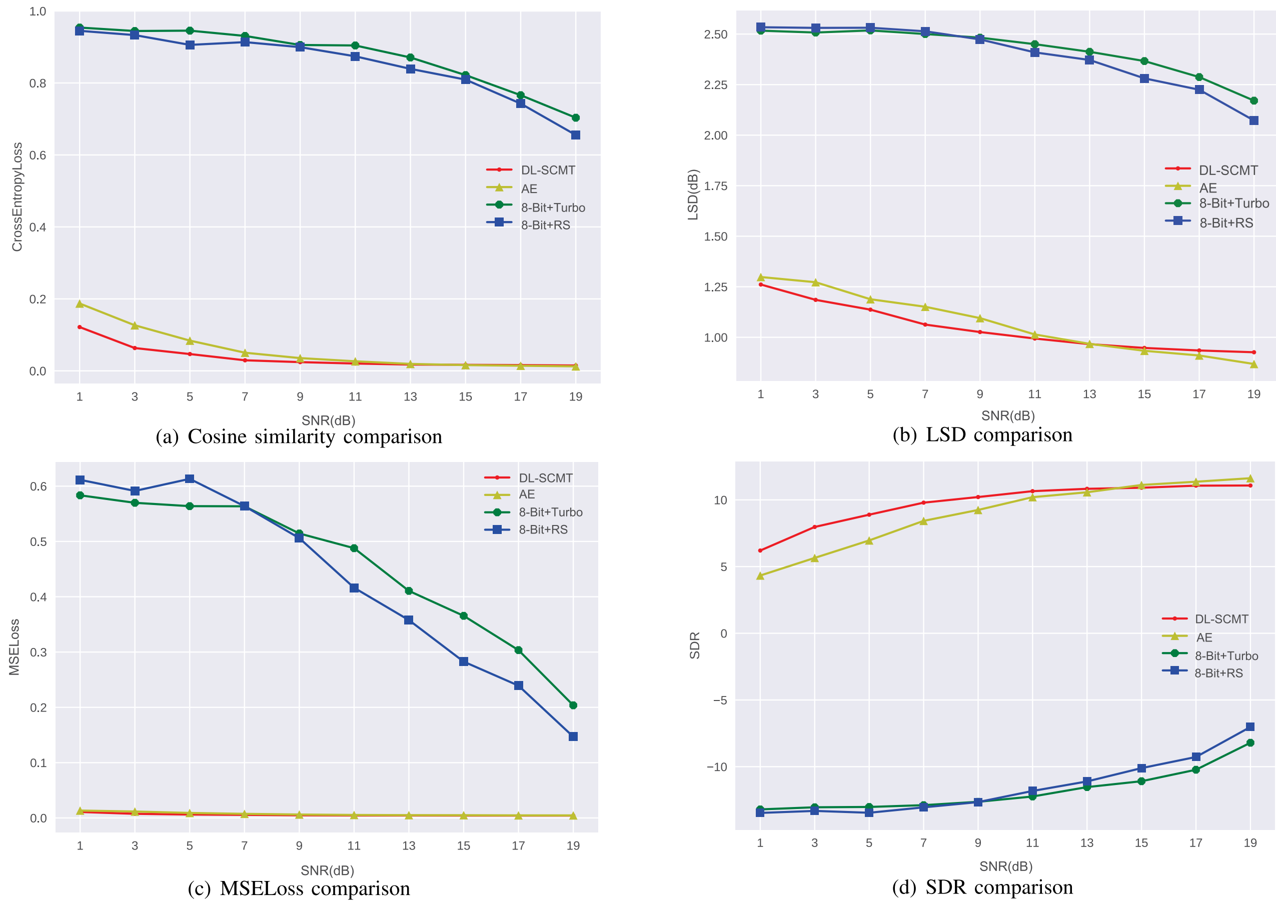


Fig. 5. Classification accuracy of DL-SCMT and conventional communication methods for physical channels with different SNR values.



(a) Cosine similarity comparison

(b) LSD comparison

(c) MSELoss comparison

(d) SDR comparison

Fig. 6. Comparison of DL-SCMT and traditional communication methods in SDR, LSD, MSELoss and cosine similarity indicators.

classification network, respectively, and $Equal(\cdot)$ is the numerical comparison function.

IV. Experiment

This section conducts experiments on our proposed semantic communication model enabled by deep learning for temporal data. The first part of the experiment compares the performance of model groups of noise reduction and classification networks trained in physical channel environments with different SNR values on the classification task, and then selects the parameters of the best noise reduction and classification network models as the parameters of the DL-SCMT model to support subsequent experiments. The second part of the experiment compares the DL-SCMT model with traditional communication methods in terms of classification accuracy, cosine similarity, MSELoss, SDR and LSD metrics.

The data in this experiment are collected from the signals sensed by intelligent fabrics. We simulate the behaviour of the user on the intelligent fabric by using a linear module with a fixed coil at different distances from the magnetic intelligent fabric. The data is divided into 3 distances, i.e. 3 categories, with each pull period being $4.5s$, and the $STM32$ is the master control of the acquisition terminal and collects potential signals at a sampling rate of $20Hz$, with potential signals in the range of $\pm 1000uV$. There are roughly 10,000 acquisition points for each type of signal, with 100 acquisition points per signal frame. When training the model, 70% of the total data is used as the training set, 10% as the validation set and 20% as the test set. When used, we randomise the starting point of the data frames to obtain the signal frames, in an attempt to classify the interactions based solely on the random interaction data determined by the length of the signal frames.

For the conventional communication, we designed two communication baselines, as shown in Table I; the source coding uses fixed-length coding (8-bit), and the data preprocessing scales and shifts the potential signal value to 0-200, and one byte can satisfy one signal characterization. Reed-Solomon (RS) coding [21] and Turbo coding [22] are used for channel coding. The maximum length of each block of RS is set to 255, and the number of ecc symbols is set to 30. The turbo coding rate is $1/3$, and the modulation and demodulation method is 64-QAM. In the model training and comparison experiments, the physical channels are used AWGN channels.

The performance of the noise reduction network and classification network trained under different SNR values of the physical channel on the classification task is shown in Fig 4. The accuracy of all models increases gradually as the SNR value increases, i.e. the noise in the signal decreases. Around SNR = 15 dB, the accuracies all reach near 100%. The noise reduction and classification networks trained at SNR = 6 dB have better robustness; at SNR = 1 dB, the model achieves 82% accuracy; and at SNR values of 5 dB and

7 dB, the accuracy of this model is the highest compared to others. Therefore, we selected the noise reduction module and classification network trained at SNR = 6 dB as the best model parameters for semantic communication in this experiment, so as to determine the parameters of the DL-SCMT model and provide support for subsequent comparison experiments.

The classification accuracies of DL-SCMT and traditional communication methods are shown in Fig 5 where AE is the network with the noise reduction module deleted on DL-SCMT as a way to show the effect of the noise reduction network, and the subsequent experimental AE model representation is consistent with this. The classification accuracy of each communication method gradually increases as the noise in the physical channel is reduced. The accuracy of DL-SCMT is the highest for all SNR values from 1 dB to 7 dB; where SNR = 1 dB, the accuracy is 82%; when SNR = 7 dB, the accuracy is 98%. In the case of high physical channel noise, the noise reduction network in DL-SCMT does improve the classification accuracy compared to the AE model. At SNR values of 9 dB and beyond, both the DL-SCMT and AE models have nearly 100% accuracy, while the conventional model can only reach 100% near SNR of 23 dB, indicating that our proposed DL-SCMT model outperforms the conventional model and the AE network also possesses good noise robustness.

The comparison of DL-SCMT and conventional communication methods in terms of SDR, LSD, MSELoss and cosine similarity index is shown in Fig 6. Fig 6(a) shows the comparison of the cosine similarity index, the smaller the value, the better the reconstructed signal. The DL-SCMT keeps the lowest value, and as the SNR value grows, the AE model gets closer to the DL-SCMT and the value of the traditional communication method decreases. Fig 6(b) shows the LSD metrics, where DL-SCMT works best between SNR values of 1 dB and 11 dB; the AE model works better at SNR values of 13 dB and beyond, although the DL-SCMT effect keeps decreasing continuously. This indicates that the noise reduction network slightly affects the performance of the AE model at larger SNR values, however, it still has performance advantages compared to the traditional communication method. Fig 6(c) shows the MSELoss metric, which is already extremely low for DL-SCMT and AE networks at low SNR values; however, the traditional communication method only gradually decreases when the SNR value decreases. Fig 6(d) shows the SDR metric, the larger the metric, the lower the reconstructed signal noise power; between SNR values of 1 dB and 15 dB, DL-SCMT maintains the highest value; at SNR values of 16 dB and beyond, AE has a little better than DL-SCMT; the traditional communication method has always been negative, which indicates that the reconstructed signal of baseline is noisier. In summary, DL-SCMT has a very good performance in the physical channel environment with different SNR values, which is far better than the traditional communication method.

V. Conclusion

With 5G communication networks staying at the level of Internet of Everything, it is no longer possible to meet the communication requirements of users in the increasingly rich Internet smart life. Therefore, 6G proposes a human–machine–object intelligent interconnection, embedding people into the network and combining individual awareness with the network. However, current 6G research faces many challenges in terms of intelligent interconnection and intelligent ubiquity. Therefore, we propose the 6G semantic communication scheme based on intelligent fabric in transportation in-cabin scenarios, which empowers the senseless ubiquity and intelligence of intelligent fabrics to traditional communication and enhances the communication experience of users' smart interaction. Then we propose a deep learning-based semantic communication model for time-series data, which provides a semantic communication solution for the time-series data sensed by intelligent fabrics in 6GSCS-IF. Finally, we experimentally compare the performance metrics of our proposed DL-SCMT model with traditional communication methods in signal reconstruction, showing that the DL-SCMT model is much better than the traditional communication model in signal reconstruction and higher-order service effect, showing that the model has good communication noise robustness.

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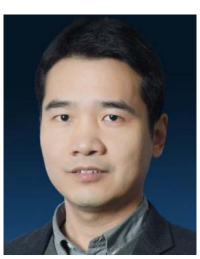
Yuan Tang is currently pursuing the Ph.D. degree with the Embedded and Pervasive Computing (EPIC) Laboratory, Huazhong University of Science and Technology. His research interests include the IoT, reinforcement learning, and cognitive computing.

Ning Zhou received the Ph.D. degree from Fudan University in 2010. He worked as a Post-Doctoral Scholar with the University of Chicago and Loma Linda University, USA, from 2013 to 2016. He is currently an Associate Professor and an Attending Physician with the Section of Cardiology, Tongji Hospital. He has published over 20 papers and has been serving as an editorial board member of many journals. He is a specialist in the field of electrophysiology and critical cardiovascular disease.

Qiao Yu is currently pursuing the Ph.D. degree with the Embedded and Pervasive Computing (EPIC) Laboratory, Huazhong University of Science and Technology. Her research interests include 3D vision and visualization.



Di Wu (Senior Member, IEEE) received the B.S. degree from the University of Science and Technology of China, Hefei, China, in 2000, the M.S. degree from the Institute of Computing Technology, Chinese Academy of Sciences, Beijing, China, in 2003, and the Ph.D. degree in computer science and engineering from The Chinese University of Hong Kong, Hong Kong, in 2007. He was a Post-Doctoral Researcher with the Department of Computer Science and Engineering, Polytechnic Institute of New York University, Brooklyn, NY, USA , from 2007 to 2009, advised by Prof. K. W. Ross. He is currently a Professor and the Associate Dean of the School of Computer Science and Engineering, Sun Yat-sen University, Guangzhou, China. His research interests include edge/cloud computing, multimedia communication, internet measurement, and networks security. He was the recipient of the IEEE INFOCOM 2009 Best Paper Award and the IEEE Jack Neubauer Memorial Award.

Chong Hou received the B.S. degree from Peking University, Beijing, China, in 2009, and the Ph.D. degree from the Massachusetts Institute of Technology (MIT), Cambridge, MA, USA, in 2016. He was a Post-Doctoral Associate with the Research Laboratory of Electronics, MIT, from 2016 to 2018, advised by Prof. Yoel Fink. He is currently a Professor with the School of Computer Science and Engineering, Huazhong University of Science and Technology, Wuhan, China. His research interests include specialty fiber, fiber sensing, and information technology toward applications in sports and health.

Guangming Tao is a Professor with the Wuhan National Laboratory for Optoelectronics and the School of Materials Science and Engineering, Huazhong University of Science and Technology. He is the Director of the Center for Fiber Optoelectronics (CFO) and serves as the Director for the Sport and Health Initiative (SHI) at the Optical Valley Laboratory. His research interests include interdisciplinary research on fiber optoelectronics for medical fiberbot, passive thermal management, and intelligent fabric. He is the Editorial Board Member of *Laser and Optoelectronics Progress* and *Textile Research Journal*; the Associate Director of the Division of Fiber Materials and Composite Technology, Chinese Materials Research Society; and an Associate Editor of *Advanced Fiber Materials*.

Min Chen (Fellow, IEEE) has been a Full Professor with the School of Computer Science and Technology, Huazhong University of Science and Technology (HUST), since February 2012. He is the Director of the Embedded and Pervasive Computing Laboratory and the Director of the Data Engineering Institute, HUST. Before he joined HUST, he was an Assistant Professor with the School of Computer Science and Engineering, Seoul National University. His Google Scholar citations reached over 34,450 with an H-index of 89. His top paper was cited 3,825 times. He was selected as a Highly Cited Researcher from 2018 to 2021. He received the IEEE Communications Society Fred W. Ellersick Prize in 2017 and the IEEE Jack Neubauer Memorial Award in 2019. He is the Chair of the IEEE Globecom 2022 eHealth Symposium. He is the Founding Chair of the IEEE Computer Society Special Technical Communities on Big Data.