Large AI Model Empowered Multimodal Semantic Communications

Feibo Jiang, Member, IEEE, Yubo Peng, Li Dong, Kezhi Wang, Senior Member, IEEE, Kun Yang, Fellow, IEEE, Cunhua Pan, Senior Member, IEEE, Xiaohu You, Fellow, IEEE

Abstract-Multimodal signals, including text, audio, image and video, can be integrated into Semantic Communication (SC) for providing an immersive experience with low latency and high quality at the semantic level. However, the multimodal SC has several challenges, including data heterogeneity, semantic ambiguity, and signal fading. Recent advancements in large AI models, particularly in Multimodal Language Model (MLM) and Large Language Model (LLM), offer potential solutions for these issues. To this end, we propose a Large AI Model-based Multimodal SC (LAM-MSC) framework, in which we first present the MLMbased Multimodal Alignment (MMA) that utilizes the MLM to enable the transformation between multimodal and unimodal data while preserving semantic consistency. Then, a personalized LLM-based Knowledge Base (LKB) is proposed, which allows users to perform personalized semantic extraction or recovery through the LLM. This effectively addresses the semantic ambiguity. Finally, we apply the Conditional Generative adversarial networks-based channel Estimation (CGE) to obtain Channel State Information (CSI). This approach effectively mitigates the impact of fading channels in SC. Finally, we conduct simulations that demonstrate the superior performance of the LAM-MSC framework.

Index Terms—Semantic communication; multimodality; LLM; MLM; knowledge base.

I. INTRODUCTION

In Weaver and Shannon's pioneering works, communication systems can be categorized into three levels of complexity, ranging from low to high [1]:

 Technical level: This aspect relates to the efficiency and accuracy of the communication system. It involves the sender transmitting information (such as a message or signal) to the receiver, overcoming any noise or interference that may lead to errors or loss of information.

Feibo Jiang (jiangfb@hunnu.edu.cn) is with Hunan Provincial Key Laboratory of Intelligent Computing and Language Information Processing, Hunan Normal University, Changsha, China.

Li Dong (Dlj2017@hunnu.edu.cn) is with Changsha Social Laboratory of Artificial Intelligence, Hunan University of Technology and Business, Changsha, China.

Kezhi Wang (Kezhi.Wang@brunel.ac.uk) is with the Department of Computer Science, Brunel University London, UK.

Kun Yang (kunyang@essex.ac.uk) is with the School of Computer Science and Electronic Engineering, University of Essex, Colchester, CO4 3SQ, U.K., also with Changchun Institute of Technology.

Cunhua Pan (cpan@seu.edu.cn) is with the National Mobile Communications Research Laboratory, Southeast University, Nanjing 210096, China.

Xiaohu You (xhyu@seu.edu.cn) is with the Frontiers Science Center for Mobile Information Communication and Security, National Mobile Communications Research Laboratory, Southeast University, Nanjing, China, and also with the Purple Mountain Laboratories, Nanjing, China.

- 2) Semantic level: This level of communication refers to the meaning of the message being transmitted. It ensures that the sender and receiver understand and interpret the message in the same way, which is crucial for effective communication.
- 3) Effectiveness level (Pragmatic): This level observes the impact of the communication on the receiver. Effective communication should accomplish its intended goal or purpose, making a difference in the receiver's thoughts, behaviour, or emotions.

The rapid integration of Artificial Intelligence (AI) and the Internet of Things (IoT) has led to the emergence of intelligent applications, such as holographic communication, and the Internet of Everything (IoE). These trends are driving the evolution of communication systems toward Semantic Communication (SC) [2], which integrates communication with semantic information, concentrating on the "meaning" behind transmitted bits to enable more intelligent and adaptive communication services. Consequently, SC is capable of operating at higher levels (i.e., semantic or effectiveness levels) within Weaver's communication framework. Typically, the SC system comprises five components, including the semantic encoder, channel encoder, channel decoder, semantic decoder, and the Knowledge Base (KB). These components can be implemented by applying neural networks which have favourable feature extraction capabilities, which can be trained to maximize system capacity and minimize semantic errors during transmission [3].

Currently, the data to be transmitted is typically multimodal for advanced applications, such as metaverse and mixed reality. As a result, the multimodal SC system is highly required to facilitate SC across multiple modes, including text, voice, images, videos, and more. In conventional SC systems, a single SC model is designed to handle only one type of unimodal data. That is, transmitting multimodal data requires using multiple separate unimodal SC systems, with each catering to a specific type of multimodal data, as shown in Fig. 1(a). This implies that each device must deploy multiple SC systems, potentially leading to significant overheads and inefficiencies. Therefore, we aim to design a multimodal SC system that is capable of processing various modal data by using a single, unified multimodal SC model, as depicted in Fig. 1(b).

A. Challenges of Multimodal SC

To better achieve multimodal SC, we identify and summarize several challenges currently faced by multimodal SC systems:

Yubo Peng (pengyubo@hunnu.edu.cn) is with School of Information Science and Engineering, Hunan Normal University, Changsha, China.



(a) Traditional unimodal SC system

(b) Multimodal SC system

Fig. 1: Traditional unimodal SC system versus multimodal SC system.

- 1) Data heterogeneity: A multimodal SC should be capable of handling the simultaneous transmission of heterogeneous data, including text, images, videos, and even specialized or rare file formats in various forms. Then, the target tasks associated with this data can be quite complex, involving machine translation, image recognition, and video analysis, among others. Additionally, consideration should be given to semantic alignment when extracting semantic features from multimodal data, ensuring a uniform understanding across different multimodal data.
- 2) Semantic ambiguity: On one hand, multimodal SC systems may encounter issues such as semantic errors or misunderstandings when transmitting multimodal data from one modality to another, resulting in semantic ambiguity. On the other hand, each party in communication has distinct knowledge backgrounds and may focus on different semantic information. As a result, it may cause an inconsistent understanding of the semantic information of the same data between different parties, contributing to semantic ambiguity.
- 3) Signal fading: Fading channels exhibit variations in signal strength over time, influenced by factors like environmental conditions, distance, and interference. This fluctuation adds a layer of complexity to the accurate and meaningful exchange of information between senders and receivers. In SC, fading channels may give rise to distortions or errors in message transmissions [3]. Consequently, these disturbances can result in the loss of critical information or the alteration of intended semantics, further complicating the process of retrieving and reestablishing personalized semantics.

B. Advantages of Large AI Model in Multimodal SC

Recent advancements in Deep Learning (DL) have enabled the development of large AI models for multimodal data and Natural Language Processing (NLP), resulting in models with enhanced capabilities in these domains, such as Multimodal Language Model (MLM), e.g., Composable Diffusion (CoDi) [4], and Large Language Model (LLM), e.g., GPT-4 [5]. These large AI models have the following common advantages for SC:

- Accurate Semantic Extraction: With billions of parameters, large AI models can learn intricate representations, providing high-quality semantic extraction of input data.
- Rich Prior/Background Knowledge: Pre-trained on vast datasets like ImageNet, Audioset, and Wikipedia, large AI models gain extensive domain knowledge, exhibiting excellent world model capabilities.
- Robust Semantic Interpretation: With their robust generation capabilities, large AI models can effectively interpret diverse semantic information, even when faced with semantic noise.

Furthermore, the continuous enhancement of computational power and the growth in data volume have allowed these sophisticated AI models to be successfully implemented across various industries, providing potential solutions for achieving multimodal SC.

C. Our Contributions

In this paper, we propose a Large AI Models-based Multimodal SC (LAM-MSC) framework to address the previously mentioned challenges. Our contributions can be summarized as follows:

- 1) We introduce the MLM-based Multimodal Alignment (MMA). Specifically, we utilize the CoDi model to process multimodal data and convert them into text modality data, which is more easily understood and requires less transmitted data with higher information density. MMA facilitates the synchronized generation of interwoven modalities by constructing a shared multimodal space during the diffusion process. As a result, heterogeneous multimodal data can be transformed into unimodal data while maintaining semantic alignment.
- 2) We propose a personalized LLM-based Knowledge Base (LKB). Concretely, we regard the GPT-4 model as a global shared KB capable of providing robust text analysis and semantic extraction. Then, users can create their own personalized prompt bases and utilize them to fine-tune the global GPT-4 model, thereby obtaining a personalized local KB. This personalized KB can extract

the most relevant semantics from the text modality data for each sender and reconstruct the text data according to specific requirements. Consequently, the accuracy of semantic extraction and conveyance is enhanced, effectively reducing semantic ambiguity.

3) We apply a Conditional Generative adversarial networksbased channel Estimation (CGE) technique to obtain Channel State Information (CSI). In particular, we employ Conditional Generative Adversarial Networks (CGAN) to predict the CSI of fading channels, utilizing pilot sequence as the conditional information fed into the CGAN. With the acquirement of the CSI, the channel effect on transmitted signals is transformed from multiplicative noise to additive noise, which can be readily accommodated by neural network-based channel decoders. This approach effectively mitigates the impact of fading channels in SC.

The remainder of this paper is structured as follows: First, we introduce the CoDi for multimodal data and GPT-4 for personalized KB. Next, we present the LAM-MSC framework and its key components, including MMA, LKB, and CGE methods. Subsequently, we provide simulations to evaluate the performance of the LAM-MSC framework. Finally, we conclude the paper.

II. CODI FOR MULTIMODAL DATA AND GPT-4 FOR PERSONALIZED KB

A. CoDi for Multimodal Data

CoDi is an innovative MLM introduced by Microsoft, capable of generating output modalities (text, image, video, audio) from any combination of input modalities. The key components of CoDi include [4]:

1) Latent Diffusion Model: Diffusion models capture data distributions by emulating the diffusion of information over time. The latent diffusion model reduces computational costs by learning the distribution of latent variables related to data.

2) Composable Multimodal Conditioning: To achieve semantic alignment across multiple modalities, CoDi calibrates encoders to project inputs from any modality into a unified space using "bridging alignment". Text is used as the "bridging" modality for effective semantic alignment.

3) Composable Diffusion: CoDi is designed to be composable and integrative, allowing the construction of distinct modality-specific diffusion models that can be integrated. Image, video, audio, and text diffusion models are trained independently and combined via a novel latent space alignment mechanism.

4) Joint Multimodal Generation by Latent Alignment: To achieve cross-modal attention between diffusion flows during joint generation, "potential alignment" is used. CoDi trains cross-attention weights and context encoders using paired text-image, text-audio, and audio-video data, allowing for the simultaneous generation of various modal combinations unseen during training.

B. GPT-4 for Personalized KB

1) GPT-4-Based Global KB: GPT-4, introduced by OpenAI in 2023 [5], is among the most advanced LLMs, succeeding

GPT-3 and GPT-3.5 as the latest evolution in the GPT series. This model adopts the transformer architecture and boasts approximately 100 billion parameters. Trained on vast text corpora containing trillions of words, GPT-4 excels at learning intricate language representations. The model's capabilities in multi-modal knowledge synthesis, semantic summarization, continuous learning, and scalability make it highly suitable for automatically populating and expanding KBs from unstructured data. As a result, GPT-4 is utilized as the global KB. While GPT-4-based global KBs are built on general textual data, fine-tuning enables them to adapt to more specialized domains, such as medicine, finance, or communication.

2) *Fine-Tuning-Based Personalized KB:* Large AI models can be updated with few samples, allowing adaptation to specific tasks such as personalized applications. There are four primary fine-tuning methods to transform the GPT-4-based global KB into a personalized KB for individuals:

- Adapter Tuning [6] trains a few parameters in small networks called adapter modules, inserted after each layer in the original LLM. By fixing pre-trained model parameters and training only adapter module parameters, computational costs are reduced while preserving pretraining knowledge.
- *Prefix Tuning* [6] is a parameter-efficient method that trains a small set of parameters called the "prefix" to modify the input for the pre-trained model. The prefix optimizes task-specific input, requiring less computational resources than full model fine-tuning.
- *Prompt Tuning* [7] allows users to guide the behavior of LLMs and align their responses by prompt for specific requirements or objectives. By carefully designing and refining prompts, it is possible to improve the quality, relevance, and accuracy of the generated outputs.
- Layer-wise Relevance Analysis (LoRA) [8] aims for transparent and interpretable fine-tuning by adding a low-rank matrix to each pre-trained model layer and fine-tuning it for target tasks while keeping the original pre-trained weights fixed.

III. IMPLEMENTATION OF MULTIMODAL SC

We propose the LAM-MSC framework, leveraging the power of large AI models to solve the previously mentioned challenges (i.e., data heterogeneity, semantic ambiguity, and signal fading). The key to the LAM-MSC framework is that we introduce CoDi model to facilitate the transformation of heterogeneous multimodal data into a singular unimodal format. We choose text data as the unimodal format due to its various benefits, including human readability, high information density, limited redundancy, and lower storage demands compared to video or audio formats [9]. Moreover, using text data as the unimodal format enables us to apply GPT-4 as the KB, enhancing the accuracy of semantic extraction and the interpretability of data recovery.

A. LAM-MSC Framework

For implementing the SC of multimodal data, we consider the LAM-MSC framework that combines the large AI models



Fig. 2: The illustration of the proposed LAM-MSC framework.



Fig. 3: A data flow example within the proposed LAM-MSC framework can be demonstrated through an image transmission scenario. Here, the sender, Mike, attempts to convey the semantics of "He and Jane in a playful pose".

as a solution. As shown in Fig. 2, the workflow of the LAM-MSC framework is summarized as follows:

1) Modal Transformation Based on MMA: For the input multimodal data, which includes image, audio, and video data, MMA is utilized to convert these data into text data while maintaining semantic alignment. The corresponding text data can effectively capture the original modal data's content. For example, as illustrated in Fig. 3, the raw sent data consists of a photograph featuring the sender (presumed to be Mike) and the receiver (presumed to be Jane) playing in a garden. The raw image is then converted into a text description: "A boy and a girl in a playful pose. The boy has blond hair and is wearing a white shirt and a blue tie. The girl has brown hair and is wearing a white shirt and a red bow tie. The background is a colorful garden". Thus, by applying MMA, we manage to transform multimodal data into unimodal data while ensuring semantic alignment.

2) Semantic Extraction Based on LKB: For the text data obtained through modal transformation, senders typically aim to transmit only the key information that expresses their

intended message or the parts they find most important while omitting redundant information they deem irrelevant for the receiver. This personalized key information can be referred to as semantics. Hence, LKB is used to personalize the text and thus obtain personalized semantics. As depicted in Fig. 3, initially, the raw text does not encompass personalized information. However, by integrating the sender's intention, user information, and interests, the LKB extracts personalized semantics "Jane and me in a playful pose". This description represents the identities of the sender and receiver and indicates that the sender's focus is primarily on the "two people" in the photograph rather than the background or dressing up.

3) Data Transmission Based on CGE Assisted-SC: SC starts with a semantic encoder that extracts meaningful elements or attributes from raw data, aiming to transmit this semantic information as accurately as possible to the receiver. Then, the channel encoder modulates the semantically encoded data into complex-valued input symbols suitable for wireless communication. To mitigate the effects of the fading channel, the CGE is employed to acquire the CSI, which in turn

transforms the multiplicative noise into additive noise. This conversion reduces the complexity involved in the channel decoder's recovery of transmitted signals. Next, the channel decoder is utilized to perform signal demodulation while overcoming the additive noise. Finally, the semantic decoder performs semantic decoding to retrieve recovered semantics (e.g., "Jane and I playfully posing"). Although the physical channel impairments cause slight differences between recovered semantics and original content, overall meaning consistency is maintained.

4) Semantic Recovery Based on LKB: The receiver may not understand the recovered semantics directly since the personalization of received messages is specific to the sender rather than the receiver, which can lead to semantic ambiguity issues. Hence, similarly, the LKB is adopted to change the decoded semantics into the personalized semantics for the receiver according to the personalized prompt base of the receiver. As shown in Fig. 3, the LKB adjusts the recovered semantics according to the receiver's user information (e.g., identify). As a result, the recovered semantics is transformed into personalized semantics for the receiver, Jane, resulting in the text "Mike and I playfully posing".

5) Modal Recovery Based on MMA: Similar to modal transformation, MMA is utilized to achieve modal recovery, meaning it converts text data back into the original modal data. However, it is important to note that we only evaluate the consistency between the recovered and original modal data in terms of semantics rather than data components level details. As illustrated in Fig. 3, the raw image shows "Mike and Jane playing in a garden". However, the recovered image only displays "Mike and Jane are playing at a certain place". This is because the sender's primary intention is on the semantic aspect – "Mike and Jane play together" – rather than specific details regarding the background or clothing.

B. MMA

In the proposed LAM-MSC framework, MMA performs the multimodal transformation. Referring to Fig. 2, the workflow of MMA can be summarized as follows:

1) Modal Transformation: In the sender, the MMA transforms multimodal data, including image, audio, and video data, into unimodal data-text data. Specifically, first, each type of multimodal data is encoded by its respective encoder. Then, the encoding results of the multimodal data are fed into the condition encoder, which processes them according to the target modality being transitioned to, in this instance, the text modality. Finally, the processed results from the condition encoder are input into the text diffusion model to generate corresponding text data that maintains semantic consistency with the original multimodal data.

2) Modal Recovery: From the receiver's perspective, the MMA facilitates the transformation of personalized semantics (text modality data) back into the original multimodal data. Specifically, the process is as follows: First, the personalized semantics are fed into the text encoder to obtain the text encoding. Next, the text encoding is input into the conditional encoder, which processes the data based on the target modality

being recovered, such as image, audio, and video data. Finally, the processed result from the conditional encoder is input into the diffusion model of the target modality, which encompasses image, audio, and video diffusion models. This generates corresponding modality data that ensures semantic consistency with the input personalized semantics.

C. LKB

LKB primarily consists of two components: The global GPT-4 model and the personalized prompt base. The descriptions of these components are summarized below:

1) Global GPT-4 KB: The GPT-4 model boasts outstanding capabilities in NLP, allowing it to perform precise semantic extraction and restoration from textual data according to specific requirements. With numerous parameters and multihead attention mechanisms, GPT-4 excels at accurate knowledge representation, allowing it to comprehend semantics and knowledge structures with precision. Additionally, GPT-4 has been pre-trained using extensive datasets, which has enabled it to store rich prior/background knowledge and achieve strong generalization abilities across different domains. Hence, the GPT-4 model is used as the shared global KB for all users, serving as a "global" model consistently utilized across a diverse array of applications.

2) Personalized Prompt Base: As discussed in Section II-B, there are four primary methods for achieving personalization in GPT-4 models. However, methods such as adapter tuning, prefix tuning, and LoRA involve adjusting the GPT-4 model's structure. These modifications necessitate users to possess specific professional knowledge and require their devices to be equipped with substantial resource support. Clearly, this is an unrealistic demand for the majority of common users.

Therefore, we adopt prompt tuning as the preferred method for users to personalize their GPT-4 models. This approach only requires users to construct a personalized prompt base containing their unique information, such as nation, language, identity, interests, and so on. Consequently, users only need to input this prompt base along with the text data into the global GPT-4 model, after which the personalized semantics are generated.

D. CGE

One of the primary methods for mitigating the effects of fading channels in wireless communication is to leverage a link's known channel properties, specifically the CSI. As illustrated in Fig. 2, we utilize the CGE to acquire CSI. This information greatly enhances the accuracy of semantic transmission in the wireless channel. Notably, the pilot sequence, received signal, and CSI are treated as dual-channel images, representing the real and imaginary components of a complex matrix. Consequently, the task of channel estimation can be reframed as an image-to-image translation problem [10].

Traditional GAN is built upon the idea of training a generator and a discriminator network in an adversarial manner. Although the generator learns a mapping from random noises to actual data, this method exhibits instability and randomness, thereby rendering it unsuitable for channel estimation. To address this issue, we propose to extend GAN by employing CGAN which can map a conditional input to its corresponding real data. In CGE, we use CGAN to learn the mapping relationship between the received signal, the pilot sequence, and the CSI. Following the same structure as a typical GAN, the CGAN also features two neural networks that serve as a generator and a discriminator during offline training, as detailed in Section V-E. Upon completion of the training, the trained generator can be utilized to estimate CSI from the conditional input (i.e., the received signal and pilot sequence), as depicted in Fig. 2.

Therefore, by obtaining CSI, the channel effect on transmitted signals transitions from multiplicative noise to additive noise. This change can be easily handled by neural networkbased channel decoders [11]. Overall, this approach effectively mitigates the influence of fading channels in the SC model.

E. Training for the LAM-MSC Framework

In the proposed LAM-MSC framework, several models are employed, including CoDi, GPT-4, the CGAN, and the SC model (including semantic and channel models). Among these, CoDi and GPT-4 are the models with well-established pretrained weights, which negate the need for additional training. As a result, our primary focus lies in providing comprehensive details about the training schemes for the CGAN and the SC model.

1) Training for the CGAN: In a CGAN, the generator and the discriminator are trained in an adversarial manner, as described below:

- a. Data preprocessing: Collect the training dataset, which includes the pilot sequence, the received signal, and the CSI. As previously mentioned, the pilot sequence, the received signal, and the CSI are processed as dual-channel images for training. The pilot sequence and the received signal serve as input data, while the CSI is used as label data.
- b. Discriminator training: Begin by training the discriminator in the CGAN. Supply it with both real CSI samples and generated CSI samples produced by the generator. Calculate the discriminator's loss using a chosen loss function (e.g., binary cross-entropy) and update its weights to minimize this loss. Thus, the discriminator can recognize whether the input CSI samples are real or generated.
- c. Generator training: Once the discriminator is trained, proceed to train the generator. Generate synthetic CSI samples using the pilot sequence and the received signal as inputs for the generator. Pass these generated samples through the discriminator and compute the generator's loss. Update the generator's weights to maximize this loss, with the goal of deceiving the discriminator.
- d. Alternating training: The discriminator and generator are alternatively trained until the system converges. During each training iteration, update the discriminator's weights to better differentiate between real and generated CSI samples, and improve the generator's weights to create more realistic CSI samples that can deceive the discriminator.

2) Training for the SC Model: Notably, in the SC model, the semantic model comprises the semantic encoder and decoder, while the channel model consists of the channel encoder and decoder. The training process can be summarized as follows:

- a. To jointly train the channel encoder and decoder, mutual information is used as the objective function. This approach helps counter noise or fading effects during transmission, thereby preventing signal distortion [3].
- b. The BLEU metric is utilized as the optimization function for the semantic encoder and decoder in order to achieve effective learning. This optimization function is informed by the difference between the original and recovered semantics, guiding the model's learning process to minimize discrepancies and preserve semantic integrity.
- c. A crossed-training strategy is implemented, alternating between the channel encoder/decoder and semantic encoder/decoder models. Specifically, the channel model is initially trained, followed by freezing its parameters. Subsequently, the semantic model is trained. Next, the semantic model's parameters are frozen, and the channel model training is resumed. This process can be repeated until the entire SC and channel models converge [3].

IV. SIMULATION RESULTS

A. Problem Formulation

We focus on an end-to-end data communication scenario that encompasses the transmission of various data types, including images, audios, and videos. These multimodal data are transformed into unimodal data (i.e., text data) by MMA. Moreover, we incorporate a BERT and cosine similarity-based semantic evaluation method [12]. Specifically, we first utilize the MMA+LKB to obtain the personalized semantics from the raw and recovered multimodal data. Then, BERT is used for text encoding on the text data. Next, we calculate the cosine similarity between the text encodings of the original and recovered multimodal data. Finally, a predetermined cosine similarity threshold is used to assess the accuracy of SC.

B. Simulation Settings

First, we present the evaluation datasets for the multimodal SC as follows:

- VOC2012 (image dataset) [13]: This dataset comprises 17,125 RGB images across 20 categories.
- LibriSpeech (audio dataset) [14]: This corpus contains approximately 1,000 hours of 16 kHz English speech readings.
- UCF101 (video dataset) [15]: This action recognition dataset consists of realistic action videos from YouTube, spanning 101 action categories.

Second, the SC model is designed for text modal data. Thus, we apply the transformer as the network architecture. The channel model, which encompasses channel encoding and decoding along with wireless channel configuration, adopts settings similar to those presented in [3]. For the CGAN, the architectures of the generator and the discriminator adopt similar designs presented in [10] Finally, the threshold for cosine similarity is set at 0.6. This indicates that the transmitted semantics is considered accurate only when the cosine similarity between the text encodings exceeds 0.6. The transmission accuracy is defined as the ratio of semantically correct transmitted samples to the total number of transmitted samples.

C. Evaluation Results

The evaluation results are illustrated in Fig. 4 and Fig. 5. In Fig. 4, we observe that the transmission accuracy of multimodal SC increases as the SNR improves. Additionally, the audio modal data has the highest, while the video modal data has the lowest accuracy, which can be attributed to their inherent complexity. Fig. 5 clearly indicates that the transmission accuracy declines with an increasing cosine similarity threshold. Furthermore, the transmission accuracy at an SNR of 25 dB is notably higher than that at an SNR of 10 dB.



Fig. 4: Transmission accuracy of multimodal SC under different SNRs.

In conclusion, the evaluation results validate the effectiveness of the proposed LAM-MSC framework in achieving multimodal SC based solely on a uniform SC model (depicted in Fig. 2), while maintaining the semantic consistency between the raw and recovered multimodal data. In addition, in our simulations, we observe that when using the conventional transmission method, a video requires 3,114,800 bits, an image needs 597,792 bits, and audio necessitates 1,472,224 bits. However, utilizing LAM-MSC, only the uniform semantic coding is transmitted, which remarkably reduces the consumption to only 32,768 bits.

V. CONCLUSION

In this paper, we first introduced the challenges faced by multimodal SC. Then, as a solution, we presented a LAM-MSC framework that incorporates MMA, enabling transformations between multimodal and unimodal data while preserving semantic consistency. Next, a personalized LKB was proposed in LAM-MSC, allowing users to undertake individualized



Fig. 5: Transmission accuracy versus cosine similarity threshold.

semantic extraction or recovery, effectively tackling semantic ambiguity issues in transmitted data. In addition, we applied CGE to obtain the CSI and thus reduce the impact of fading channels in SC. Finally, simulations effectively demonstrated the superior performance of the proposed LAM-MSC framework in processing multimodal data communication.

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BIOGRAPHIES

Feibo Jiang received his B.S. and M.S. degrees in School of Physics and Electronics from Hunan Normal University, China, in 2004 and 2007, respectively. He received his Ph.D. degree in School of Geosciences and Info-physics from the Central South University, China, in 2014. He is currently an associate professor at the Hunan Provincial Key Laboratory of Intelligent Computing and Language Information Processing, Hunan Normal University, China. His research interests include artificial intelligence, semantic communication, Internet of Things, and mobile edge computing.

Yubo Peng received the B.S. degree from Hunan Normal University, Changsha, China, in 2019, where he is currently pursuing the master's degree with the College of Information Science and Engineering. His main research interests include federated learning and semantic communication.

Li Dong received the B.S. and M.S. degrees in School of Physics and Electronics from Hunan Normal University, China, in 2004 and 2007, respectively. She received her Ph.D. degree in School of Geosciences and Info-physics from the Central South University, China, in 2018. She is currently an associate professor at Hunan University of Technology and Business, China. Her research interests include machine learning, Internet of Things, and mobile edge computing.

Kezhi Wang received the Ph.D. degree in Engineering from the University of Warwick, U.K. He was with the University of Essex and Northumbria University, U.K. Currently, he is a Senior Lecturer with the Department of Computer Science, Brunel University London, U.K. His research interests include wireless communications, mobile edge computing, and machine learning.

Kun Yang received his PhD from the Department of Electronic Electrical Engineering of University College London (UCL), UK. He is currently a Chair Professor in the School of Computer Science Electronic Engineering, University of Essex, leading the Network Convergence Laboratory (NCL), UK. He is also an affiliated professor at UESTC, China. Before joining in the University of Essex at 2003, he worked at UCL on several European Union (EU) research projects for several years. His main research interests include wireless networks and communications, IoT networking, data and energy integrated networks and mobile computing. He manages research projects funded by various sources such as UK EPSRC, EU FP7/H2020 and industries. He has published 400+ papers and filed 30 patents. He serves on the editorial boards of both IEEE (e.g., IEEE TNSE, IEEE ComMag, IEEE WCL) and non-IEEE journals (e.g., Deputy EiC of IET Smart Cities). He was an IEEE ComSoc Distinguished Lecturer (2020-2021). He is a **Cunhua Pan** received the B.S. and Ph.D. degrees from the School of Information Science and Engineering, Southeast University, Nanjing, China, in 2010 and 2015, respectively. He was a Research Associate with the University of Kent, Canterbury, U.K., from 2015 to 2016. He held a postdoctoral position with the Queen Mary University of London, London, U.K., from 2016 and 2019, and was a Lecturer from 2019 to 2021. He has been a Full Professor with Southeast University since 2021. He has published over 120 IEEE journal papers. His research interests mainly include reconfigurable intelligent surfaces (RIS), intelligent reflection surface, ultrareliable lowlatency communication, machine learning, UAV, Internet of Things, and mobile-edge computing.

Xiaohu You received the M.S. and Ph.D. degrees in electrical engineering from Southeast University, Nanjing, China, in 1985 and 1988, respectively. Since 1990, he has been with the National Mobile Communications Research Laboratory, Southeast University, where he is currently the Director and a Professor. From 1999 to 2002, he was a Principal Expert of the C3G Project, responsible for organizing China 3G Mobile Communications Research and Development Activities. From 2001 to 2006, he was a Principal Expert of the China National 863 Beyond 3G FuTURE Project. Since 2013, he has been a Principal Investigator of the China National 863 5G Project. He has contributed over 200 IEEE journal articles and two books in the areas of adaptive signal processing and neural networks, and their applications to communication systems. His research interests include mobile communication systems, and signal processing and its applications. Dr. You was selected as an IEEE Fellow for his contributions to the development of mobile communications in China in 2011. He was a recipient of the National 1st Class Invention Prize in 2011.