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Semantic Slicing across the Distributed Intelligent 6G Wireless Networks

Lauri Lovén
Center for Ubiquitous Computing
University of Oulu
Oulu, Finland
lauri.loven@oulu.fi

Hafiz Faheem Shahid
Center for Wireless Communication
University of Oulu
Oulu, Finland
faheem.shahid@oulu.fi

Le Nguyen
Center for Machine Vision and Signal Analysis
University of Oulu
Oulu, Finland
le.nguyen@oulu.fi

Erkki Harjula
Center for Wireless Communication
University of Oulu
Oulu, Finland
erkki.harjula@oulu.fi

Olli Silvén
Center for Machine Vision and Signal Analysis
University of Oulu
Oulu, Finland
olli.silven@oulu.fi

Susanna Pirttikangas
Center for Ubiquitous Computing
University of Oulu
Oulu, Finland
susanna.pirttikangas@oulu.fi

Miguel Bordallo López
Center for Machine Vision and Signal Analysis
University of Oulu
Oulu, Finland
miguel.bordallo@oulu.fi

***Abstract*—In the age of the Internet of Things (IoT) and the expanding computing continuum, it's crucial to manage and share resources at the edges of networks. This position paper presents a new concept known as 'semantic slicing'. This approach harnesses the power of artificial intelligence (AI), wireless networks, edge computing, and sensing technologies to enable novel applications, optimize resource allocation, and streamline data processing and decision-making across complex systems spanning the computing continuum. Semantic slicing applies a deep understanding of the data and specific application requirements to intelligently allocate resources and distribute processing tasks in the computing continuum. This strategy allows for the creation of systems that are not only more efficient and responsive, but also better equipped to adapt to a variety of applications and services.**

I. Introduction

Imagine a world where data sources and streams, originating from IoT and cyber-physical devices, are actively revised on-the-go, adapted, and sliced down to the essentials of sensing according to the changing needs and requirements of applications and users in the computing continuum based on their semantic context. The advent of 6G wireless networks, coupled with advances in AI, edge computing, and multimodal sensing, presents unprecedented opportunities for enhancing the performance and responsiveness of complex systems. While these technologies enable the development of intelligent, adaptive, and highly efficient systems that can cater to the diverse needs of various applications and services, the key challenge for harnessing their full potential lies in the effective allocation of resources and the ability to make informed decisions based on semantic understanding of data.

In this position paper, we introduce the concept of *semantic slicing*, an innovative approach that integrates AI, wireless networks, edge computing, and sensing, to optimize resource allocation, data processing, and decision-making across complex systems. Semantic slicing builds upon the idea of network slicing in 5G and 6G networks and extends it by incorporating AI-driven semantic understanding of data and application requirements. By intelligently allocating resources and distributing processing tasks based on the semantic context, semantic slicing enables more efficient and responsive systems that can adapt to diverse applications and services.

Semantic slicing goes beyond traditional slicing approaches by considering the context and semantics of the data. This allows for the creation of multiple virtual verticals within a shared physical infrastructure, each with its own set of characteristics and requirements. Different types of slicing have been proposed, such as network slicing [1], the scheduling and allocation of computing resources, and end-to-end slicing of both computational and communication resources [2]–[4]. However, semantic slicing specifically addresses the unique challenges of data management in the computing continuum, where data is streaming within a dynamic and distributed net-

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work of nodes with multiple applications and users, each with their own complex requirements, restrictions, and domains of data under their control.

II. Background Technologies

Different background technologies pave the way for the creation of distributed intelligence in 6G wireless networks. These include artificial intelligence (AI), wireless networks (with a focus on 6G), edge computing, and sensing. Understanding these technologies and their roles in semantic slicing is crucial for grasping the potential of this approach.

Artificial intelligence (AI) provides the foundation for the semantic understanding of data [5]. AI techniques, such as machine learning and deep learning, can be used for data analysis, pattern recognition, and decision-making across multiple components of an intelligent system, including both the data and the organization of the system itself. In the context of semantic slicing, AI algorithms are employed to analyze the preprocessed data and develop a semantic understanding of the data. This understanding allows for intelligent allocation of resources and distribution of processing tasks, ultimately leading to improved decision-making and more efficient system performance [6].

Wireless networks enable the transmission of data between devices without the need for wired connections. The evolution of wireless networks has led to significant advancements in data rates, latency, and capacity, with 6G being the next-generation communication technology that promises to revolutionize the way we interact with digital systems [7]. One of the key concepts in 5G and 6G networks is network slicing, which allows operators to dynamically allocate resources (e.g., bandwidth, latency, and processing capabilities) to different services based on their specific requirements [8]. Semantic slicing extends this idea by incorporating AI-driven semantic understanding of the data and the application requirements, leading to more intelligent and efficient resource allocation.

The computing continuum is a spectrum of computing environments and architectures that are used for deploying and managing applications, algorithms and system functions, etc., as services [9]. It encompasses different computing paradigms, including centralized cloud computing, decentralized edge computing, and distributed fog (or local edge) computing. Each of these paradigms has its own characteristics and benefits as well as limitations and challenges, particularly when it comes to resource management.

Multimodal distributed sensing refers to the process of collecting data from the environment through different fixed and mobile sensors in a coordinated manner. In many applications, understanding the context and meaning of the sensor data is vital for effective decision-making and resource management [10]. Semantic slicing addresses this need by employing AI algorithms to analyze the extracted features from the raw set of sensor data and develop a semantic understanding through a shared representation. This understanding enables the system to focus on specific aspects of the data or prioritize certain types of applications that are more critical or sensitive, leading to more intelligent and efficient system operation.

III. Semantic slicing concepts

In the context of 6G wireless networks, the integration of AI, wireless networks, edge computing, and sensing technologies plays a crucial role in realizing the potential of semantic slicing. By combining the capabilities of these technologies, semantic slicing can intelligently manage and process data in a distributed manner, ensuring efficient resource allocation and responsive decision-making across various applications and services. Several key semantic slicing concepts, as listed in Table I, build upon these foundational technologies, exploring how they work together to enable distributed, intelligent, adaptive systems.

Semantic data acquisition involves collecting data from various sensors, such as video feed from cameras, radio signals from radars and communication devices, temperature, humidity, pressure, or other physical quantities from environmental sensors, or movement, biosignals, or other individual characteristics from personal sensors. On typical data acquisition, preprocessing is performed to extract relevant features or patterns from the raw sensor data, allowing for more compact representation and highlighting the meaningful aspects of the data. Edge computing, including on-device local edge or Multi-Access Edge Computing (MEC) hosted by access networks, can be utilized in this step to process the data closer to the source, which reduces latency and requirements for bandwidth.

Semantic understanding is achieved by applying a variety of AI algorithms, such as machine learning or deep learning, to analyze preprocessed data and develop a semantic interpretation of data. This involves recognizing specific events, patterns, or relationships in the data that are important for a particular application. By understanding the semantics of the data, the system can make more informed decisions about resource allocation and processing tasks.

Semantic network slicing can be applied to wireless networks to intelligently allocate resources such as bandwidth, latency or processing capabilities, based on semantic understanding of the data and requirements of different applications or services. This might involve prioritizing certain types of data or applications that are more critical or sensitive, leading to more efficient and effective resource utilization.

Semantic distributed processing distributes computing tasks across the continuum, based on semantic understanding, location of data and data sources, and the specific requirements of the tasks. This can improve the efficiency and performance of the system, enabling it to better support diverse applications in the network.

Semantic decision-making and action allows the system to prioritize decisions or actions based on the semantic understanding of the application. This may include prioritizing the triggering of alarms, adjusting system parameters, or providing only timely insights to users. Semantic understanding of the

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TABLE I
SEMANTIC SLICING CONCEPTS AND KEY ENABLERS

Concepts	Key enablers	Challenges
Semantic data acquisition	Sensor slicing [11] [12], data slicing [13] [14] [15] [16]	Scalability, real-time processing, data heterogeneity
Semantic understanding	AI: feature slicing [16] [15] and parameter slicing [17]	Model complexity, interpretability, domain adaptation
Semantic network slicing	Network slicing [18] [19] [20]	Dynamic resource allocation, isolation, quality of service (QoS) guarantees
Semantic distributed processing	Multimodal sensing [10], Resource slicing [21] [22] [23]	Load balancing, fault tolerance, latency
Semantic decision-making and action	AI [5], Computing continuum [9], Multimodal distributed sensing [10]	Responsiveness, context awareness, security and privacy

data makes decision-making more effective and timely, leading to improved system performance.

IV. Semantic Slicing Framework

The implementation of semantic slicing should integrate the concept through data and is pipelines, AI, edge computing, wireless networks, and sensing itself. Our proposed framework consists of several key components that work together to enable the efficient allocation of resources, distributed processing, and informed decision-making based on the semantic understanding of data. Figure 1 shows an example on how semantic slicing propagates through all layers of the computing continuum, from sensing to data.

Data slicing is a technique used in data analysis, particularly in the context of big data and machine learning. It involves partitioning the data into smaller subsets or "slices" based on certain criteria or dimensions, such as time, location, or specific features. This enables more focused analysis and can lead to more efficient processing and better understanding of the data. Data slicing include horizontal and vertical partitioning [13], sharding, and replication [14]. Li et al. defined a slicing of a table as an attribute partition and a tuple partition, while Chung et al. considered a slice as a subset of examples in a dataset with common features [15] [16]. While data slicing is an important aspect of data preprocessing and analysis, it does not address the broader challenges of resource allocation, distributed processing, and decision-making across complex systems. Semantic slicing builds upon the idea of data slicing by integrating it with AI, wireless networks, edge computing, and sensing technologies to enable a more comprehensive approach to managing and processing data in complex systems.

AI Model slicing is a technique used in the context of artificial intelligence and machine learning, where a trained model is partitioned into smaller, more focused models that cater to specific subsets of the data or tasks. This is often achieved by identifying the most relevant neurons, layers, or weights in the model and removing or pruning the less relevant components. Model slicing can lead to significant improvements in model efficiency, scalability, and adaptability, as it allows for more focused and resource-efficient processing of specific data subsets or tasks. This has been approached using both feature space slicing [16] [15] and model/parameter slicing [17]. While these approaches offer several advantages in the context of AI, its primary focus is on improving the efficiency and performance of individual models, rather than addressing the broader challenges of resource allocation, data processing, and decision-making across complex systems. Semantic slicing, on the other hand, aims to address these challenges by integrating AI-driven semantic understanding of data with resource allocation and distributed processing techniques. In this context, model slicing can be considered as a complementary technique that can be used in conjunction with semantic slicing to optimize the performance of AI models and further enhance the overall efficiency and responsiveness of the system.

Network slicing is a concept primarily associated with 5G and 6G networks, where a single physical network infrastructure is virtually partitioned into multiple independent logical networks, each catering to specific service requirements. This enables more efficient resource allocation and better support for diverse applications with varying needs in terms of latency, bandwidth, and reliability. Different ideas have been suggested, such as an edge computing architecture that tailors needed network resources at the edge cloud [18], a three-layer architecture based on services [19], or the leverage of edge-and cloud for slicing [20]. While network slicing offers significant improvements in resource allocation and network management, it does not inherently consider the semantic understanding of data or the specific requirements of individual applications. Semantic slicing extends the idea of network slicing by incorporating AI-driven semantic understanding of the data and application requirements, leading to more intelligent and efficient resource allocation that can better adapt to the diverse needs of various applications and services.

Resource access slicing refers to the technique of dynamically allocating and managing access to multiple resources within a network based on specific criteria, such as application requirements, priority levels, or resource constraints. This approach enables more efficient use of resources, as it allows for the selective activation, deactivation, or sharing

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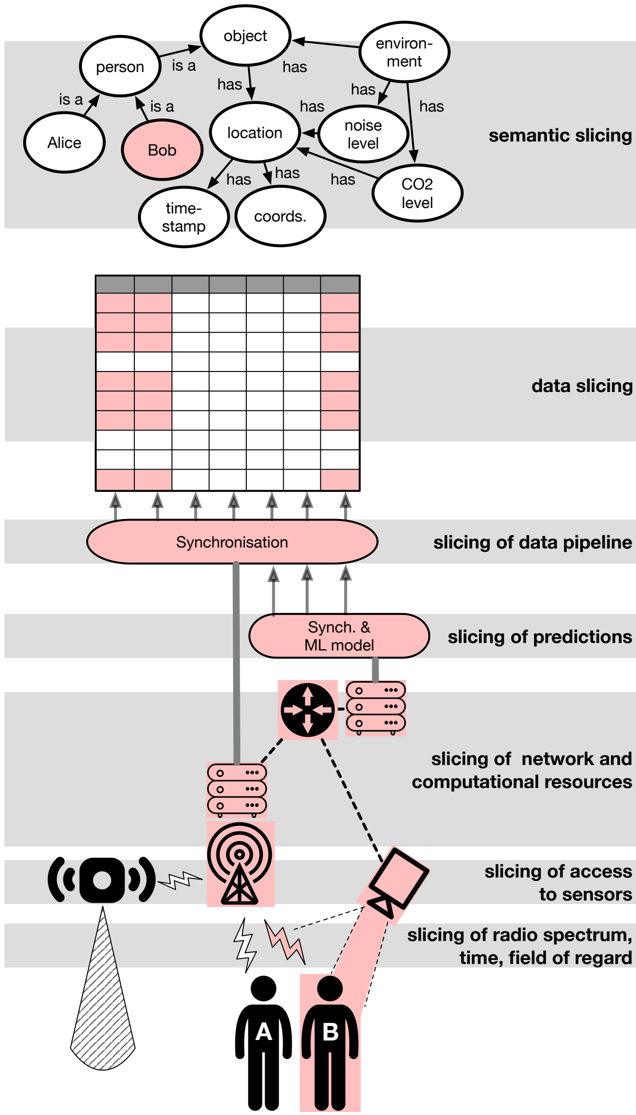

Fig. 1. **Semantic slicing example.** An individual is labeled to be followed with high priority. Accordingly, the high-level data frame is sliced based on observations (rows) as well as observed and predicted features (columns). The slicing propagates through data streams and predictions, raising priority of certain streams and models over others, and across the communication and computation infrastructure in the computing continuum, to originating components and sensors, finally prioritizing the use of fundamental resources in sensing.

meet the varying demands of different applications or services. Resource access slicing can be particularly beneficial in situations where there are limited resources, or where multiple applications compete for access to the same resources [21]–[23]. By integrating this technique with AI-driven semantic understanding it becomes possible to create more intelligent and adaptive systems that can efficiently handle the diverse requirements and challenges of various applications and domains while optimizing sensor resource utilization.

Sensor slicing is a technique that involves partitioning data collected from sensors into smaller, more focused subsets or ”slices” based on specific criteria, such as time, location, or particular features [11], [12]. This approach enables more efficient and targeted analysis of sensor data, leading to better understanding and utilization of the information. Furthermore it promotes resource-efficiency and sustainability through using common sensors for various applications and services. Sensor slicing can be particularly useful in applications where large volumes of data are generated by multiple sensors, as it allows for the isolation and analysis of relevant data segments based on the specific needs of the application. By combining sensor slicing with techniques such as AI-driven semantic understanding, resource allocation, and distributed processing, it is possible to develop more intelligent and adaptive systems that can better handle the diverse requirements and challenges of various applications and domains.

While there are several slicing techniques available in the literature, semantic slicing stands out due to its focus on the meaning of the data and the application, enabling more intelligent and efficient resource allocation. In order to implement the semantic slicing framework, we need a unified language to represent the heterogeneous resources in the computing continuum, such as devices and AI models, as well as defining slicing operations on network, computational resources, models, and data. Semantic schemas such as W3C Thing Description and Semantic Smart Sensor Network Ontology have been modified to specify IoT devices and neural network models [24]. We can enhance OWL-POLAR [25] to describe slicing techniques and policies that configure, operate, and prioritize the applications. These semantic descriptions can be stored in, for example, a graph database (such as GraphDB[1]) and accessed via SPARQL queries. The proposed framework is summarized in Figure 2.

V. Applications and Use Cases

Semantic slicing has the potential to benefit various applications and domains by enabling efficient isolation, prioritization, and consent management of application semantic concepts. This, in turn, improves resource allocation and distributed processing, and helps make informed decisions based on semantic understanding of the data. Some potential use cases of semantic slicing include:

Smart cities: Semantic slicing can be employed to manage the diverse and complex needs of smart city applications, such as traffic management, public safety, and environmental monitoring [26]–[28]. In this use case, semantic slicing could prioritize semantic data related to first responders or security personnel, focusing sensoring and slicing network connections and predictive models to ensure timely data capture, transmission, and processing. In an example scenario, semantic slicing can be used in a ”seeing-around-the-corner” system, which uses mmWave technology and advanced algorithms to render a virtual representation of a unseen the area of interest, helping with traffic management and security operations.

Industrial automation: In industrial settings, semantic slicing can help optimize the allocation of resources and processing tasks to ensure efficient and reliable operation of manufacturing processes, robotic systems, and other automated

[1]GraphDB: https://graphdb.ontotext.com/

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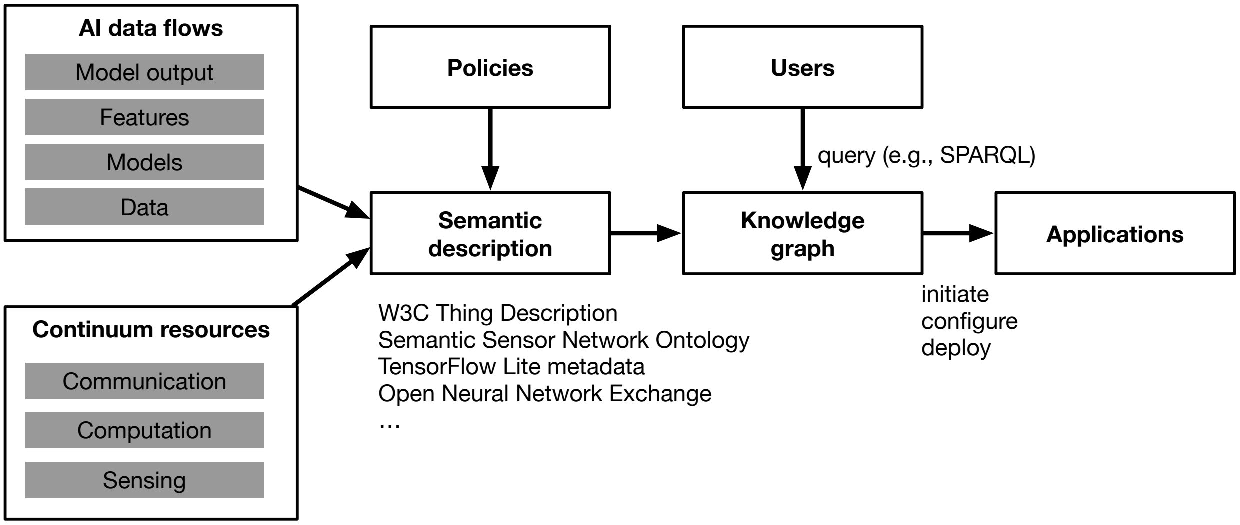

Fig. 2. Semantic slicing framework.

systems [29]. For example, semantic slicing may increase the priority of individual product batches throughout the manufacturing process, ensuring timely sensoring, transmission and analysis of product data for quality assurance purposes.

Environmental monitoring: Semantic slicing can be used for monitoring environmental parameters, such as air quality, water quality, or weather conditions [30], [31]. In this context, it can provide a more focused and efficient approach to analyzing sensor data and taking appropriate actions based on the semantic understanding of the data [26]. For example, one scenario could involve the installation of air quality and CO2 sensors as well as cameras in a building, and using this data to personalize information for a person walking around the building with a mobile device. This would be done through a decentralized approach with local edge servers and device-to-device communication. Another scenario could involve a set of mobile air quality sensors integrated in people that move around the building. The building would use the data from these mobile sensors to create a map of the air quality and CO2 levels throughout the building, with the data being aggregated to provide a more complete picture.

Healthcare: Semantic slicing can be applied to healthcare applications, such as telemedicine, remote patient monitoring, and medical imaging [32]. By understanding the context and meaning of the data, the system can prioritize critical services, allocate resources effectively, and support timely decision-making for improved patient care. Moreover, semantic slicing can provide enhanced isolation of patient data streams on a fine-grained level, improving the privacy and security of personal data sensing, processing and transmission, and furthermore, to help meeting the strict requirements by regulation/legislation [33]. In an example scenario, semantic slicing can be used in a system for unobtrusive, distributed, and multimodal measurement of vital signs, which uses a combination of sensors to enable real-time syncing and processing of vital sign data in various environments and conditions.

Connected and autonomous vehicles: In the context of connected and autonomous vehicles, semantic slicing can enable more efficient allocation of resources for communication, data processing, and decision-making. This can lead to improved safety, better traffic management, and more efficient operation of transportation systems [34]. In an example scenario, semantic slicing can be used in a vision-aided communication system that utilizes mm-wave radio technology to transmit data without the need for line-of-sight, improving communication between autonomous vehicles and other connected devices.

Internet of Things (IoT): IoT devices generate vast amounts of data that need to be processed and analyzed for effective decision-making. Semantic slicing can help manage the diverse requirements of IoT applications by intelligently allocating resources and distributing processing tasks based on the semantic understanding of the data [35], thus reducing e.g. energy consumption [36].

VI. Conclusion

In this paper, we introduced the concept of semantic slicing, an innovative approach that integrates AI, wireless networks, edge computing, and sensing to optimize resource allocation, data processing, and decision-making across complex systems. By leveraging the semantic understanding of data and application requirements, semantic slicing enables more efficient and responsive systems that can better adapt to the diverse needs of various applications and services.

We presented a high-level framework for integrating semantic slicing across these technologies and discussed potential applications and use cases in domains such as smart cities, industrial automation, environmental monitoring, healthcare, connected vehicles, and IoT. As 6G networks continue to evolve, semantic slicing has the potential to play a crucial role in shaping the future of wireless communication and related technologies, enabling more intelligent, efficient, and adaptive

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systems that can cater to the ever-growing demands of our digital world.

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