Environment Knowledge Supported RAN Control for 6G Campus Networks

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***Abstract*—In this paper, the authors present a Radio Access Network (RAN) concept for future mobile communication systems beyond 5G. The concept is based on knowledge of the environment. The three conceptual applications RAN authentication, beam steering, and channel estimation are presented and their added value with respect to 6G development goals is outlined. The concept is explained by means of an intralogistic use case of a fully automated warehouse. Based on this, the concrete steps for implementation in a laboratory setup are described and further research steps are shown.**

***Index Terms*—6G, mmWave, RAN, ray-tracing, sensor fusion, green ICT, campus network, EI**

I. Introduction

The evolution of the current 5G mobile communications system into a possible sixth generation of mobile communications promises, among other things, higher data rates, improved security and resilience, while increasing efficiency and meeting sustainability goals [1]. One key aspect in achieving the targeted data rates is the use of millimeter Wave (mmWave) frequencies enabling larger bandwidths. However, the higher frequencies also have drawbacks that need to be addressed in order to operate efficiently and in line with sustainability goals. The development of new architectures or concepts together with big data analytic is very promising [2]. Big data collected from a wide variety of sources such as sensors can be analyzed to obtain knowledge about the environment in order to improve or make useful predictions within new concepts of mobile communication systems.

At the same time, a clear trend can be seen in the industry. Digitization is being strongly driven forward by trends such as Industry 4.0. Internet of Things (IoT) devices create a digital perception and make their data available. Data is accessible via standardized data pools, which is ensured by new standards such as Open Platform Communication Unified Architecture (OPC UA) or Message Queue Telemetry Transport (MQTT). Building on this, new concepts are being implemented, such as the digital twin. This new digitized world that is to be found in the industry of the future can in turn also be used by other technologies for optimization. This motivates us to explore how this data can support the mobile communication of the future.

In the following paper the authors propose an approach to improve mmWave communication with knowledge about the environment. Here, the special case is considered that the mobile communication system is a campus network. In this case, access to environmental information is more likely to be available, while in the industrial environment, extensive sensing by IoT sensors is more or less standard.

In the end, the authors will conclude their work and provide an outlook on how the concept will be implemented and evaluated in the future.

The approach is developed successively in three different stages, first by the example of network authentication, followed by a beam steering case, and last a channel estimation scenario. In addition, hardware setups are proposed for the evaluation of the different approaches.

II. Related Work

This work mainly covers four research categories in the field of mobile communication systems. In the field of 6G, this includes research in the area of adaptive radio access through sensor information, development of sustainable mobile radio solutions, deployment of mmWaves and security. Wei *et al.* address the most important aspects of the future generation of mobile communications in [1]. Thereby they discuss in detail the requirements that the use of higher frequency bands imply. In this context, the necessity of beam forming and steering is almost obvious. In addition to beam forming and steering, the demand for optimized radio resource management becomes extraordinary. Wei *et al.* argue that the demand for outstanding mobility management becomes unprecedentedly high and that interference management becomes essential in scenarios with dense coexistence of links. Moreover, Wei *et al.* consider Edge Intelligence (EI) as important paradigm for future mobile networks. Accordingly, EI is expected to significantly improve the performance of network services and the efficient use of network resources, reduce a mobile operator's Capital Expenditure (CAPEX) / Operational Expenditure (OPEX), and reduce network complexity.

Salehi *et al.* adopt such an EI approach in [3] and develop it further to the extent that they design Mobile Edge Computing Center (MEC). MEC executes fusion-based deep-learning algorithms to leverage multi-modal data collected from various sensors in the infrastructure. Using this approach, Salehi *et al.* improve the beam selection speed by 95%.

Just like in [3], similar constructions are presented in [4] and [5] where out-of-band information is leveraged to either reduce beam selection overhead by enhanced beam selection or predict blockage conditions between transmitter receiver pair. These approaches have their legitimization in the broad field of Vehicle-to-Infrastructure (V2I) communications in particular by the fact that herewith also the big objective of a sustainable and resource efficient 6G is tackled by improving the systems energy efficiency. This topic is very strongly discussed in [6], [7], and [8] in terms of beamforming architectures and energy-saving potential. Wei *et al.* also refer in [1] to the realization of energy-efficient and carbon emission-reduced mobile networks as a crucial task from a societal perspective.

Hoydis *et al.* introduce in [9] Sionna, a differentiable open-source link-level simulator with native integration of Neural Networks (NNs) and full GPU acceleration. Sionna enables rapid prototyping as well as realistic industry-grade evaluations. With the SionnaRTX extension it is even possible to reconstruct scenes, get the corresponding channel impulse responses by ray-tracing and use them immediately for link-level simulations.

In [10], Nishio *et al.* use computer vision methods to demonstrate how wireless communications from the leverage of external sensor systems. Their work illustrates two important use cases for this work among others. In the first scenario, the computer vision output is used to predict radio frequency (RF) performance. The second scenario goes a step further by making predictive decisions for wireless communications based on computer vision applications.

III. Knowledge Support Concept

Mobile communication systems use several mechanisms to control and manage the physical radio access. In 5G initial beam assignment and beam tracking is done via sending periodic Synchronization Signal (SS)-Burst packets and determining the best received beam. Channel estimation is done via attaching known pilot symbols to the frame and do equalization at the receiver.

This approach is very general and always justified when dealing with an unknown and poorly predictable environment. However, it causes additional system overhead. A campus network is a kind of closed environment, and there are some that are equipped with tracking systems, computer vision cameras, and much more, such as those used in a fully automated warehouse with Automated Guided Vehicles (AGVs) or in a fully automated production line with autonomous robots. The information generated by these infrastructure mounted sensors increases the level of knowledge about the environment. The idea is that this knowledge can be leveraged to support the control mechanism of the RAN and help to reduce or even avoid overhead it contains. In order to protect private data and maintain the integrity of the units, the RAN and the infrastructure sensors are kept separate. For this reason, a mediating unit, the so-called Knowledge Agent (*KA*), is introduced. The *KA* provides the following services to the RAN:

- Verify User Equippment (UE) position for authentication
- Provide a new best beam as soon as the UE has moved
- Provide channel estimates as soon as the environment has changed

The procedures are described in more detail in the following sections.

In addition to reducing overhead and therefore increasing efficiency, the external knowledge source can also be used for validation, increasing the overall security and resilience of the RAN.

Figure 1 shows an example of a complete implementation of the concept based on the warehouse scenario. The sensors required for the operation of the AGV system that are integrated into the campus infrastructure, such as Ultra Wideband (UWB) positioning and computer vision, are grouped together in the *Sensor Infrastructure* block. It provides its output in the form of the Sensor Infrastructure State Vector (*Sens-state*). In addition to the sensor value, it also contains information about the type, mounting position and orientation of the respective sensor.

The *RAN* itself is viewed as a sensor as well, it produces the RAN State Vector (*RAN-state*) as output. It contains sensory data about the air interface like Channel State Information (CSI), Received Signal Strength Indicator (RSSI), Angle of Arrival (AoA), and additionally the regarding antenna position as well as orientation.

Leveraging on the known mounting positions of the different sensors and the antenna positions, the *KA* embedded *Sensor Fusion* function performs a translation of the attached sensors into one common frame of reference. This information is aggregated and held in the form of the Environment State Vector (*Env-state*).

The Ray-Tracing-Model (*RTM*) performs a simulation of the channel based on the currently captured environmental state. From this and by the combination with the route information from the *AGV-Routing-System*, the relationships and mutual influences of the different actors can be derived and passed to the *KA* as the Environment Information Vector (*Env-information*). The *KA* combines the incoming status vectors with the respective position into a unique fingerprint. Those are stored in a database to gradually create a unique fingerprint *Map* of the radio cell. The *KA* develops a control strategy for the RAN and provides this information with the RAN Control Vector (*RAN-control*). In addition, it is possible to predict the channel into the future, which enables improved handover management. This makes the system more resilient, as it is able to detect channel blockages ahead of time and prevent them through appropriate beam and channel selection.

This control is of course very dependent on the quality of information provided by the *Sensor Infrastructure* and the *RAN*. Therefore, the control concept described is designed to fall back on the usual procedure in case the accuracy of these

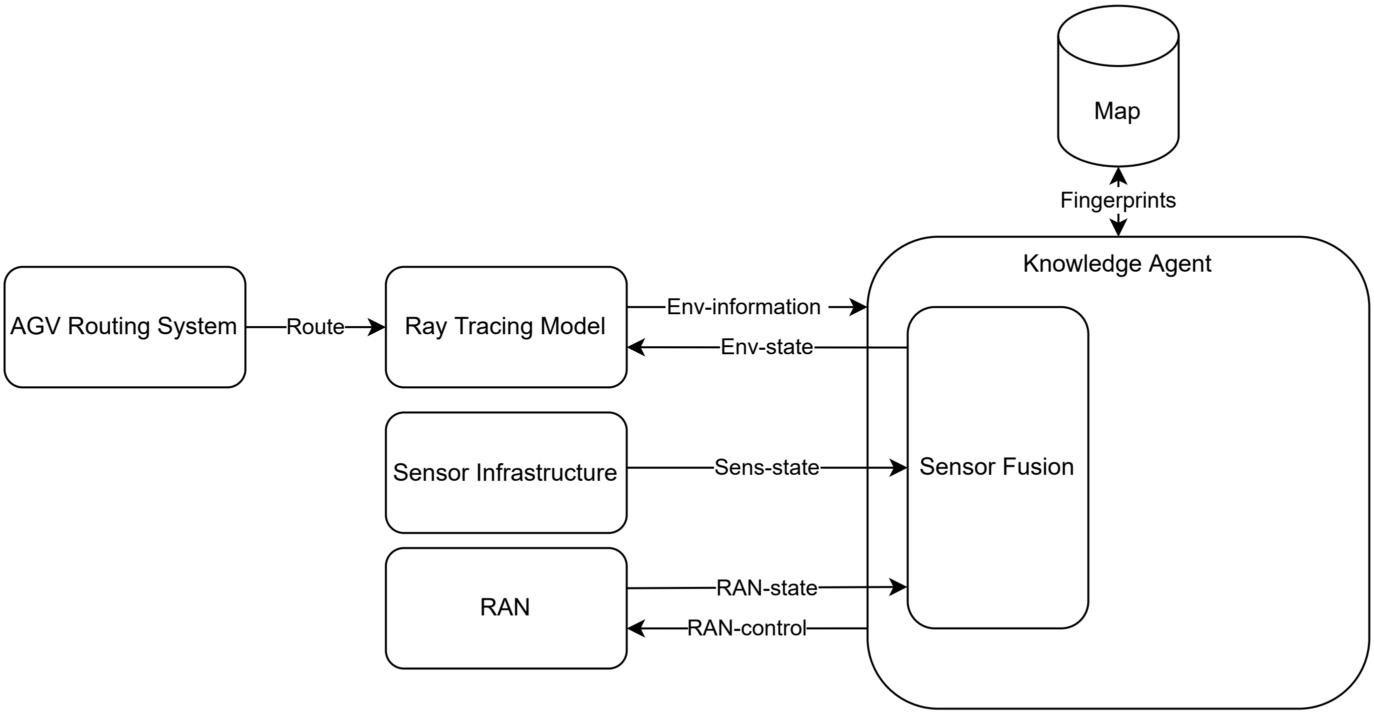

Fig. 1. Knowledge supported RAN control

data sources cannot be guaranteed. Such a dynamic approach makes the system independent to sensor system failures.

In the following sections three use cases are employed to develop this concept step by step. The first and second cases are without a *RTM*. The third case uses the *RTM*.

A. RAN Authentication

When a new UE attempts to access the network, it is unclear whether the UE's location comes from inside the campus complex and can therefore be considered trustworthy, or whether it comes from outside and poses a potential risk. Securing a campus network can be a difficult task. Physically, the infrastructure is often very well protected by security personnel. However, the air interface is difficult to control, especially in large and cluttered complexes, it provides a potential entry point for attackers. Detecting and preventing such attempts in the first place makes a big difference in terms of security.

Figure 2 shows the implementation of the knowledge support concept described above for the case of RAN authentication. It starts with the UE in question sending a random access request to the RAN. The RAN then signals its verification request to the *KA* by means of the *RAN-state* and implicitly asks for verification. The *KA* requests the current *Sens-state* from the infrastructure and fuses them internally. The verification process is performed by comparing the two UE position information including the position fingerprint. The final result is send back to the RAN which decides weather or not to proceed with the standard RACH procedure.

In this way, unknown or physically absent participants can be identified and kept away from the network. Even the attempt is detected. In addition, an accepted connection can be permanently tracked and validated to further enhance security. This approach complements existing security measures, and by applying this method only to the physical layer, information and processes are encapsulated, increasing confidentiality on the one hand and resilience to upper layer attacks on the other.

B. Beam Steering

Frequencies in the mmWave spectrum offer immense contiguous bandwidths, enabling very high data rates. This is interesting especially for moving UEs in a industrial context e.g. an AGV or a autonomous robot. With a high data rate link such devices can be controlled from the edge, reducing complexity, weight, power consumption and cost. However range and propagation of mmWave limit their use. As a countermeasure commonly beamforming is used. To be effective, however, very narrow beams, known as pencil beams, must be formed and precisely steered. A common technique is to frequently iterate through a series of beams and have the UE report which beam was best received. This may be possible at lower frequencies with a few large beams, however to spatially cover the same area with narrower beams, the number of iterations and thus the overhead increases rapidly. Due to the reduced range, the cell density also increases which drives the power consumption of the overall network as well as CAPEX.

Exploiting environment knowledge can support the RAN to steer the beams in a more accurate way and thus help to enable the use of mmWaves. Figure 3 shows the sequence

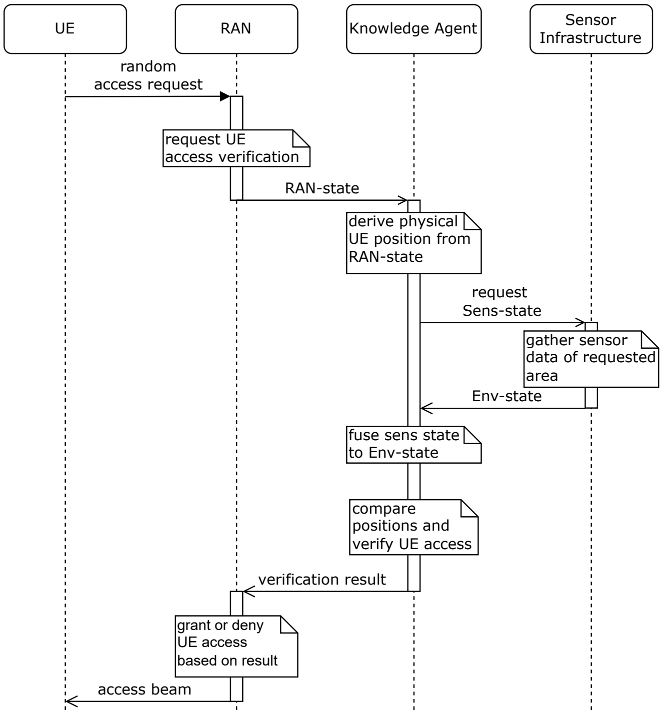

Fig. 2. Knowledge supported RAN access sequence

for the case of a moving UE. The *KA* continuously monitors the *RAN-state* and *Sens-state* vectors for relevant changes. As soon as a position change is detected, it selects a new beam corresponding to the new position. For this purpose a fixed code book is used and the corresponding entry is transmitted to the RAN via the *RAN-control*.

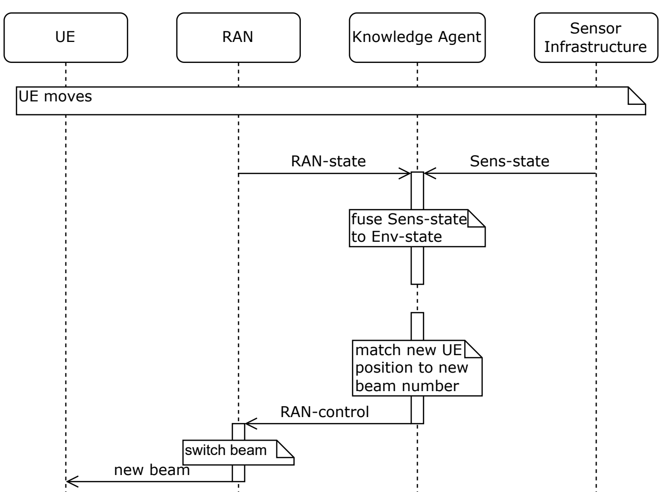

Fig. 3. Knowledge supported beam steering sequence

By applying this concept, the previously mentioned overhead can be reduced or even completely avoided. However, accurate knowledge about the position of the UE is crucial for this concept to work. If only a rough position estimate is possible due to insufficient sensor information, at least the area in which the beam is swept can be narrowed down. If no sensor information is available, the system resorts to ordinary beam sweeping instead.

C. Channel Estimation

With the mmWave spectrum, the radio propagation properties transit from wave like to a more optical behavior, so that the multi-path gain decreases significantly and Line of Sight (LoS) propagation dominates, the channel becomes sparser. Recent technological developments in the field of ray tracing techniques [9] as well as increasingly faster GPU hardware, allow very short simulation times, in the range of the channel coherence time or even smaller. An implementation of such a model on an edge cloud server is potentially suitable for the estimation of sparse mmWave-channels. Consequently, the concept of the *KA* described above can be extended gainfully by such a *RTM*, in order to perform a blind channel estimation.

In the previous case, the *KA* monitored the *RAN-state* and the *Sens-state* to detect a moving UE. This is now extended to the entire environment to also detect, for example, the movement of a passive object that changes channel. Figure 4 describes the case where such a significant change occurred in the environment. Now the *KA* sends the *Env-state* for the area in question to the *RTM*. Based on this information, the model now reflects the state of the environment and can thus simulate the current communication channel, including the channel impulse response. The results obtained are passed as additional environmental information to the *KA*. This result can, of course be very complex and contain the individual channels of multiple UEs, so the *KA*'s task is to filter and extract single UE specific channel parameters and derive a *RAN-control* from it. In addition, the *RTM* provides an interface for further information sources, e.g. the routes of the AGVs. This enables the channel to be predicted into the future and allows e.g preventive detection of blockages and improved handover management.

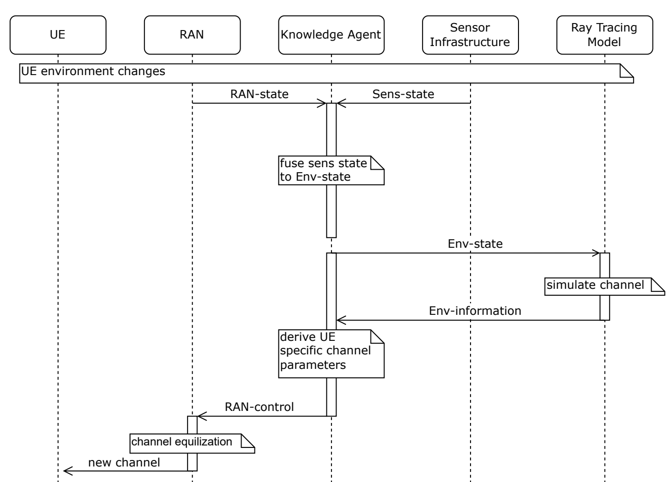

Fig. 4. Knowledge supported channel estimation sequence

IV. Conclusion

The above concept, developed and presented by the authors based on three scenarios, appears promising with respect to the challenges posed by 6G. On the one hand, it enables the use of mmWaves and the associated gain in transmission speed and capacity. On the other hand, it reduces the overhead caused by the conventional approach while increasing the security and resilience of the radio access. However, in order to assess the possibilities in more detail, the concept needs to be validated in the form of an experimental setup. An outlook on this is given in the next section.

V. Future Work

An experimental setup will implement and evaluate the knowledge-based RAN support concept based on the use cases described above. First, the warehouse scenario will be set up with a 140 GHz USRP-system with an antenna array, with a UE-equipped AGV and a sub-millimeter resolution motion detection system, and a UWB positioning system serving as an environmental sensor platform. First, the RAN authentication case is implemented and evaluated. After that, the same setup is used and configured accordingly for the beam steering case. Finally, a suitable GPU-edge-server is added to the setup to run the SionnaRTX *RTM* of the environment. Each phase of the setup is examined and evaluated for energy efficiency, security, resilience, and link speed. The entire setup will then be deployed as a demonstrator at the German Research Center for Artificial Intelligence (DFKI) in Kaiserslautern.

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References

[1] W. Jiang *et al.*, "The Road Towards 6G: A Comprehensive Survey," *IEEE Open Journal of the Communications Society*, vol. 2, pp. 334–366, 2021, Conference Name: IEEE Open Journal of the Communications Society. DOI: 10.1109/OJCOMS.2021.3057679.

[2] M. Z. Chowdhury *et al.*, "6GWireless Communication Systems: Applications, Requirements, Technologies, Challenges, and Research Directions," en, *IEEE Open Journal of the Communications Society*, vol. 1, pp. 957–975, 2020. DOI: 10.1109/OJCOMS.2020.3010270. [Online]. Available: https://ieeexplore.ieee.org/document/9144301/ (visited on 10/18/2022).

[3] B. Salehi *et al.*, *Deep Learning on Multimodal Sensor Data at the Wireless Edge for Vehicular Network*, en, Number: arXiv:2201.04712 arXiv:2201.04712 [cs, eess], Jan. 2022. [Online]. Available: http://arxiv.org/abs/2201.04712 (visited on 10/17/2022).

[4] G. Reus-Muns *et al.*, "Deep Learning on Visual and Location Data for V2I mmWave Beamforming," in *2021 17th International Conference on Mobility, Sensing and Networking (MSN)*, 2021, pp. 559–566. DOI: 10.1109/MSN53354.2021.00087.

[5] B. Salehi *et al.*, "Machine Learning on Camera Images for Fast mmWave Beamforming," en, in *2020 IEEE 17th International Conference on Mobile Ad Hoc and Sensor Systems (MASS)*, arXiv:2102.07337 [cs, eess], Dec. 2020, pp. 338–346. DOI: 10.1109/MASS50613.2020.00049. [Online]. Available: http://arxiv.org/abs/2102.07337 (visited on 10/17/2022).

[6] C. N. Barati *et al.*, "Energy and Latency of Beamforming Architectures for Initial Access in mmWave Wireless Networks," en, *Journal of the Indian Institute of Science*, vol. 100, no. 2, pp. 281–302, Apr. 2020. DOI: 10.1007/s41745-020-00170-9. [Online]. Available: https://link.springer.com/10.1007/s41745-020-00170-9 (visited on 10/17/2022).

[7] S. Dutta *et al.*, *5GMillimeter Wave Cellular System Capacity with Fully Digital Beamforming*, en, Number: arXiv:1711.02586 arXiv:1711.02586 [cs, math], Jan. 2018. [Online]. Available: http://arxiv.org/abs/1711.02586 (visited on 10/17/2022).

[8] S. Dutta *et al.*, "ACase for Digital Beamforming at mmWave," en, *IEEE Transactions on Wireless Communications*, vol. 19, no. 2, pp. 756–770, Feb. 2020. DOI: 10.1109/TWC.2019.2948329. [Online]. Available: https://ieeexplore.ieee.org/document/8883297/ (visited on 10/17/2022).

[9] J. Hoydis *et al.*, *Sionna: An Open-Source Library for Next-Generation Physical Layer Research*, en, Number: arXiv:2203.11854 arXiv:2203.11854 [cs, math], Mar. 2022. [Online]. Available: http://arxiv.org/abs/2203.11854 (visited on 10/07/2022).

[10] T. Nishio *et al.*, "When Wireless Communications Meet Computer Vision in Beyond 5G," en, *IEEE Communications Standards Magazine*, vol. 5, no. 2, pp. 76–83, Jun. 2021. DOI: 10.1109/MCOMSTD.001.2000047. [Online]. Available: https://ieeexplore.ieee.org/document/9464922/ (visited on 10/07/2022).