Abstract—Channel state information (CSI) needs to be estimated for reliable and efficient communication, however, user location information is hidden inside and can be further exploited. This article presents a detailed description of a Massive Multi-Input Multi-Output (MaMIMO) testbed and provides a set of experimental location-labeled CSI data. We first focus on the design of the hardware and software of a MaMIMO testbed for gathering multiple CSI data sets. We then show this data can be used for learning-based localization and enhanced communication research. The presented data set is made fully available to the research community. We illustrate that a CSI-based joint communication and sensing processing pipeline can be evaluated and designed based on the collected data set. Specifically, the localization output obtained by a convolutional neural network (CNN) trained on the data sets is used to schedule users to improve the spectral efficiency (SE) of the communication system. Finally, we pose promising directions for further exploiting this data set and creating more data sets.

I. INTRODUCTION

Massive Multi-Input Multi-Output (MaMIMO) is an established technology used in fifth-generation (5G) communication networks to improve reliability and spectral efficiency (SE) by means of space-time diversity [1]. In MaMIMO communication, channel state information (CSI) between a large number of antennas in the base station (BS) and serving users is accurately estimated for effective transmission. MaMIMO systems can concentrate the signal power on the user, enabling efficient use of the spectrum. Therefore, it is useful to analyze this MaMIMO channel information to further understand and improve our communication systems. The channel information can be gathered by either conducting simulations or performing real-life measurements. Existing channel simulation techniques mainly rely on stochastic geometry-based channel models or ray-tracing techniques. These models allow for the generation of a large number of channel samples at any location or configuration and are often used in data-driven approaches such as [2], [3]. However, stochastic channel models do not consider the exact geometries for a given scenario, they merely take the relative position of antenna elements into account, and all other parts of the environment are based on random clusters consisting of scatterers interacting with the wireless channel. As a result, this method is not suitable to evaluate performance in a real-life environment, which is especially important when considering joint communication and sensing applications. In addition, the virtual environment in the ray-tracing simulation must be reconstructed extremely accurately as different objects and materials will interact with propagating waves. Moreover, a ray tracer has a high computational cost, resulting in low efficiency in generating numerous data samples.

Therefore, this article aims to employ a more practical method to accumulate an accurate location-labeled CSI data set, i.e, channel measurements, considering the high accuracy and low complexity. Previously, researchers have measured and published MaMIMO channel data sets [3]–[5], however, these often contain a low number of samples or they are virtual data sets where channel measurements are performed sequentially and later combined, and these methods fail to encapsulate the actual synchronized channel state at different antennas. Thus, to measure the actual synchronized channel between MaMIMO BS and users, a MaMIMO testbed is required with real-time channel measurement capabilities over space, frequency, and time domains. Furthermore, collecting a large amount of spatially labeled CSI data samples also poses several other challenges.

One challenge of gathering the CSI for mobile users is the long duration when moving the users manually. For considering joint localization and communication in the data set, the location and CSI for a mobile user need to be captured and recorded simultaneously [6]. Another challenge is the accuracy of the spatial labels. Measuring the location of the users manually generally only reaches centimeter (cm) precision [3], can be prone to human error, and is a slow process. For outdoor locations, Global Navigation Satellite System (GNSS) can be used for labeling, leading to an average accuracy in a meter level. An improved GNSS system was used to gather the MaMIMO data set in [5], resulting in cm precision. However, their setup is only available for outdoors. An indoor solution is to utilize an indoor positioning system for millimeter (mm) precision. Then, an additional design is needed for supporting automatic measurement by integrating a proprietary positioning system with mm-level accuracy. In general, our main contributions can be summarized as follows. First, for data set generation, we develop a measurement system, using the MaMIMO testbed and a positioning system, which can collect a massive data set automatically and accurately. Second, we use the data set for two practical research problems: one is to use the CSI obtained in the communication process to localize users, the other is to enhance the communication performance by user scheduling algorithms based on localization information. Third, for data set exposure, the data set is fully open to the research community and can be accessed from the IEEE DataPort [7]. The data set is tailored to further use with data-driven approaches such as Convolutional Neural Networks.
(CNN) and has reproductively been used in other research such as in [8], [9].

The remainder of the article is as follows. The MaMIMO testbed is introduced in Section II. Afterward, the developed extensions of the testbed are presented in Section III. In Section IV, we present a detailed measurement campaign for data collection. Section V first visualizes the collected data set using the received power after Multiple-Input Single-Output (MISO) processing for different array topologies. Then, by employing a CNN, localization results are presented and further used for improving the SE of communication systems with Regularized Zero-Forcing (RZF) precoding. Section VI and Section VII pose future directions and conclude the article, respectively.

II. MASSIVE MIMO TESTBED DESIGN

In this section, an overview of the distributed KU Leuven MaMIMO testbed is presented, including the hardware and software parts.

A. The Hardware

The testbed hardware mainly consists of Software Defined Radios (SDR) from National Instruments (NI), i.e., NI USRP-2942R. In this article, they are referenced as universal software radio peripherals (USRPs). We first present the BS configuration, followed by the User Equipment (UE) description.

1) Base Station: The BS is equipped with 64 patch antennas each with an antenna gain of 6 dB. 32 USRPs are used as Remote Radio Heads (RRHs), each with two radio-frequency (RF) chains. The USRPs are controlled by a central processing unit (CPU) located in the main chassis of the BS. All devices are mounted in two server racks, combining the devices into one testbed. Fig. 1 shows a picture of the assembled BS at the back. The KU Leuven MaMIMO testbed supports flexible antenna deployment and three typical antenna topologies are created. First, in a uniform rectangular array (URA) scenario, an eight-by-eight antenna array is located in front of the Region-of-Interest (ROI). Using the URA, both a line-of-sight (LoS) and non-LoS (nLoS) data set are created. A metal blocker of 1.6 × 1.3 m, which is larger than the size of the URA, i.e., 0.56 × 0.56 m, is placed in front of the array to create the NLoS scenario. Second, for a uniform linear array (ULA) configuration, a linear array is deployed in front of the ROI. Lastly, a distributed array (DA) scenario consisting of eight arrays of eight antennas is distributed in an octagonal shape around users. A schematic overview of these three scenarios can be found in Fig. 1.

2) User Equipment: The UE is also based on the NI USRP-2942R. Since one USRP provides two RF chains, one USRP can be used for two users. The UEs are connected to a host computer using a PXIe cable for a digital link to control and forward the transmitted and received data. The UEs can be connected to the BS using coax cables in this way, the UEs can achieve a perfect synchronization in time and frequency with the BS which is a prerequisite for measurements. However, the provided UEs are static and bulky, and an automated positioning and mobility system is still required.

B. The Software: LabView MIMO Application Framework

The presented hardware is driven by the provided NI MIMO application framework. This is a LabView software project that implements all functionalities to communicate between the BS and UEs. Researchers can implement alterations or extensions directly in the provided project.

The framework uses a long-term evolution (LTE)-based frame structure using Time Division Duplexing (TDD) and numerology 0, which represents the standard parameters for the first configuration of waveforms, each subcarrier has 15 kHz, and the symbol duration is 7.1 μs. The packets are modulated using orthogonal frequency-division multiplexing. Moreover, uplink (UL) pilots are sent in different time slots.

The UL pilot is used to estimate the channel at the BS and in total 12 different UL pilot symbols are available in the framework, one for every user. Every UL pilot uses 100 subcarriers out of 1200 available subcarriers. The 12 different UL pilots are frequency interleaved, each pilot only uses one of the 12 subcarriers per resource block. Thus, all 12 users can send a pilot during the same time slot. The channel is estimated for all 64 antennas and for 100 different subcarriers. Furthermore, In-phase and Quadrature components are measured. Hence, one channel sample of one user is represented as a 64 × 100 matrix of complex values. Since channel estimation already exists in the given framework, we need to implement channel logging functionality. An example study uses the same facility but with denser data logging, such as Sakhmini et al. [10] who integrate radar sensing in a MaMIMO system.

III. TESTBED IMPLEMENTATION FOR AUTOMATED MEASUREMENTS

We describe the developed extension to automate the testbed implementation, enabling it to perform massive and accurately-labeled CSI measurements.

A. CNC-enabled Automatic User Placement

To obtain a dense data set, the positioning system should be very reliable so that the locations are still correct after the long-term operation. There are several options. First, a mobile robot can move around on the floor moving the robot around while simultaneously keeping track of its own position. Because these robots are very flexible, they lose accuracy over the duration of operation resulting in large positioning errors in long-term operation. Another option is a robotic arm whose benefit is very flexible in the 3D domain. However, they are limited in the 2D area they can cover and the cost is too high. They also over-complicate the positioning implementation. A third option is Computer Numerical Controlled (CNC) positioner. They move the user antenna with high positioning accuracy and reliability on the 2D plane. The main downside of this system is that it limits the locations of the user to the area of the CNC-positioner. However, they are relatively inexpensive and can thus be used in larger numbers to effectively increase the measurement area. In this work, we took the last option, and we used four CNC positioners simultaneously in a grid-like configuration.
The selected CNC positioner is the OpenBuilds ACRO 1515. Each positioner reliably covers a 1250 mm × 1250 mm area. Furthermore, the reported error of the positioner is less than 0.1 mm. In total four of these positioners are used, shown in Fig. 1. Custom brackets hold the legs of multiple positioners in place so that their relative position is known.

B. Automated Channel Capture Triggers using TCP

With the previously presented testbed extensions, the position and orientation of the users can be altered automatically. The next step is to automate the process of logging a CSI sample at the BS which is continuously performing channel estimation. For this purpose, the BS software is extended to receive Transmission Control Protocol (TCP) packets to automatically trigger the capture of a CSI sample. Each TCP packet contains six bytes of data, used as filenames to save the captured CSI sample. In this way, the BS can be triggered from a remote device to perform an automated measurement and label the sample accordingly. The developed code intercepts the channel estimate and writes the CSI sample to a binary file. The final process of logging position labeled-CSI samples with the testbed is as follows:

1) The user antenna is moved to a desired position by controlling the positioners.
2) When the user is at the desired location, a TCP packet containing a unique label linked to the current location is sent to the BS to start capturing the channel.
3) The BS receives the location TCP packet and will save the next channel estimation to a file labeled with this unique label.
4) The BS reports back with a TCP packet that channel capture was successful.
5) Go back to 1) until all positions have been iterated.

IV. OPEN DATA SET

The extended testbed was used to capture two data sets using three different antenna topologies, which are presented first. The first data set is called the dense data set (DDS). This data set is created by scanning the full range of the $xy$-positioners using a dense grid pattern, both in LoS and nLoS scenarios. The second data set is the nomadic data set, which focuses on the influence of moving objects in the environment.

To support transparency in research, these two data sets are published under an open-access license and can be freely downloaded through the IEEE DataPort [7]. As a result, the data can be used by other researchers to develop or validate new signal processing algorithms using measured data such as by Ranjbar et al. [9], who explore cell-free open radio access network (O-RAN) architectures using our data set. This is a major contribution to the research community as MaMIMO testbeds are not common and a freely available location-labeled MaMIMO CSI data set is rare.

A. Overview of the Scenario

The data sets were recorded in an indoor environment, the MaMIMO lab at ESAT, KU Leuven. The $xy$-positioners were placed in a rectangle in the middle of the room. The space covered by the positioners is called the ROI. For both data sets, three distinctive antenna topologies are deployed, see Fig. 1. Specifically, the three antenna deployments include

- **Uniform Rectangular Array (URA):** This array of 8 × 8 patch antennas is deployed in front of the ROI. The array is placed in the middle of the array at 1 m height above the ground. The distance between the antenna elements
center is 7 cm, and one side of the URA is 0.56 m. The array directly faces the ROI, and all possible user locations are in LoS regions of all antenna elements.

- **Uniform Linear Array (ULA):** This array consisting of $64 \times 1$ linearly arranged antennas is placed in front of and facing the ROI. The height of the patch antenna’s center is set to 1 m. With a distance of 7 cm between the centers, the resulting array has a length of 4.48 m. The array is fully in LoS conditions for all user positions.

- **Distributed Array (DA):** The 64 antenna elements are distributed over eight ULAs of eight antennas. The distance between the antenna elements center is 7 cm, thus each small ULA has a length of 0.56 m. The arrays are distributed around the ROI in an octagonal shape around the ROI. All antenna elements are placed on the same height of 1 m and are facing the middle of the ROI.

The middle of Fig. 1 shows a top-view schematic layout of the lab with the different antenna topologies. The BS’s antennas are indicated by the small squares, with each color depicting different scenarios. The center of each antenna array is always located at 2.5 m from the center of the ROI. The accuracy of this measure is $\pm 5$ mm. The waved area inside the four squares is the ROI where antennas can be moved. The user antenna is located 40 cm above the floor. For the labeling of the positions, the middle of the URA was chosen as the origin of the local coordinate system. This location is shown by the $xy$-axis in the figure. All user positions in the data set are measured in millimeters, referenced to this origin and axes, the error on these labels is less than 0.1 mm. The exact coordinates of the users and antennas are provided as a list accompanying the published data sets.

For all scenarios, the same configuration of the BS was used. The frequency is at 2.61 GHz with a transmit power of 18.5 dBm at the user, and the built-in automatic gain control at the BS is disabled. To ensure perfect synchronization between UEs and the BS, the synchronization signals were transferred by coax cables.

**B. Dense Data Set**

Existing data sets [3] collected to train localization algorithms contained up to a few thousand samples. Therefore, we aim to maximize the number of locations in the data set. The grid over which the antennas move has a resolution of 5 mm. In this way, for each positioner, a $251 \times 251$ grid was scanned. We collected 252,004 sampled positions in total using four positioners for each antenna topology. At every location in the grid, the positioner paused 0.5 s to record the channel of the users being static.

Moving the antennas to the next node in the grid and capturing a CSI sample takes for this setup on average of 0.7 s, therefore, to complete the full measurement, around 12.5 hours are required. This duration sets the limit of the size of the measurement. Long measurements require very high reliability of the measurement setup. The $xy$-positioners move cables around, decreasing the reliability of the setup as the cables get tangled. To minimize the phase change caused by thermal change and mechanical stress, we take two actions during measurements: i) the experimental environment was with constant temperature using air conditioning, and ii) equally long coax cables were used, and plenty of room was left to avoid tight bending of the coax. However, due to the large ROI, more precise phase compensation might need to be considered to have accurate channel phase values over the whole measurement duration.

For more general use, we have obtained a group of measurement data sets using our testbed, which includes different
types of indoor environments [12], such as boardroom, cafeteria, lab, corridor, and anechoic chamber, as well as outdoor environments, and different operating frequency bands, such as 900 MHz, 3.5 GHz, and millimeter-wave bands at 26 GHz. Note that they are all fully available upon request.

V. LOCALIZATION AND COMMUNICATION ANALYSIS

In this section, we discuss several applications of the DDS. First, to verify the correctness of the data set, we visualize it with the received power [11]. Next, a CNN is designed and utilized to extract location information [13]. Finally, this location information is used to develop two location-based user scheduling algorithms, resulting in all the building blocks required for a joint communication and sensing system [11]. An overview of the complete system is described in Fig. 2.

A. Visualizing MaMIMO Precoders

Using the DDS, we can visualize the beamforming patterns and visually verify the correctness of the data set. As a precoding method, maximum ratio transmission (MRT) is chosen. This beamforming technique is well understood as it maximizes the array gain. When applying MRT, we expect users with a high channel correlation to the channel of the targeted user to receive high power.

Fig. 3 shows the normalized received power for all 252,004 samples of each measurement in the DDS when employing MRT beamforming towards one user. The location of the targeted user is indicated by the red dot. Received power in these figures is normalized by dividing all powers by the maximum power measured in the area over both antenna topologies for comparisons. These figures are reprinted from [11]. The results show a consistent power distribution over the scanned area, without any discontinuities, hinting that the measurements are indeed meaningful and correct.

B. CNN-based Positioning

CNNs prove to be very efficient in learning relevant features in structured data to classify the data’s content. The obtained MaMIMO CSI contains large amounts of structured data, as a result, CNNs make a good candidate technology to process these CSI samples and infer their spatial information [14].

The CNN is used to extract features from the CSI and convert it to a low-dimensional vector, used to determine the position of the associated user. The spatial features are complex, as the CSI contains information about both direct and indirect propagation components. Fig. 2 shows the architecture of the proposed CNN. It consists of two main parts, a CNN part followed by a Fully Connected Neural Network. The CNN performs positioning with cm-accuracy, and the mean localization error of the network is 20.73 mm, 21.11 mm, and 18.04 mm for the URA, ULA, and DA LoS antenna topologies, respectively [13].

C. Localization-Enhanced Spectral Efficiency

The location information can be used to divide the users into disjoint subsets wherein the correlation between users’ channels is limited, these disjoint subsets can then be scheduled in different time slots. We propose two low-complexity scheduling methods, Angular-Based Clustering (ABC) and Distance-Enhanced Flocking (DEF) [11], which are designed specifically for systems with known users’ locations. These techniques are compared to random user selection and Semi-orthogonal User Selection (SUS) which selects users based on the mutual orthogonality of their channels [15]. SUS has a complexity of $O(M^3K)$ for $M$ BS antennas and $K$ users.

ABC uses the angle-of-arrival to sort users and then groups them in a round-robin fashion to maximize the angle between simultaneously served users. ABC has a complexity of $O(K \log(K))$. DEF traverses the users and its nearest users recursively, it then places the traversed users in different groups in a round-robin fashion. It attempts to maximize the inter-user distance. Fig. 2 gives a schematic overview of the DEF algorithm. DEF has a complexity of $O(K \log(K))$.

Fig. 4 shows the CDF of the SE of all four techniques using the URA and ULA LoS data sets using RZF precoding. It shows that ABC and DEF outperform random user selection, but perform worse than SUS; Next, a comparison between the complexity of the different schedulers is made. The complexity
of ABC and DEF grows faster than SUS in the function of the number of users but it is independent of the number of antennas at the BS. By contrast, the complexity of SUS explodes with the growing number of antennas as it was initially proposed for a scenario where $K \gg M$; however, for a Massive MIMO system, this is not a realistic expectation due to the already large amount of antennas and we expect the ratio $K/M$ to not be very large.

VI. FUTURE DIRECTIONS

In this section, we identify three research directions for further exploitation, validation, and application of the data set.

A. Applying Deep Learning on CSI Time Series

By improving the testbed to record more CSI samples per second for multiple users, we could record dense time series of MaMIMO CSI samples. When the location of a user is time-dependent, i.e. there is a large dependency between the previous position and the current position, the time-varying features between multiple CSI samples can be utilized to further improve the localization and tracking performance. To this end, Recurrent Neural Networks (RNN) and transfer learning can be used. These methods can potentially unlock mm-level localization.

B. Extensive Data Sets for Larger and More Complex Areas

Since the current work is only validated using an indoor data set spanning a relatively small area, we can improve on our current data sets. First of all, a larger area can be considered, with locations at different heights, enabling 3D localization. Next, a data set in an outdoor scenario can be recorded, optionally including measurement at different heights by mounting the user on a drone. When recording a larger data set, more complex propagation conditions can be considered, where both LoS and nLoS locations are included in the data set. In our future work, a mobile user compatible with the testbed will be developed using a compact embedded SDR, which enables large-area mobile measurement campaigns, where the user is not bounded by the synchronization cable between UE and BS. Extended data sets can also fuel important domain adaptation research, which is a key bottleneck when considering Deep Neural Network-driven physical layer design.

C. Enabling Data Set for Joint Communication and Sensing

The current bulk of work has focused separately on communication and localization. However, with longer and faster data measurements it becomes feasible to also consider the Doppler domain, and study active and passive sensing. By using the presented DDS and our proposed architecture, more flexible and advanced joint sensing and communication systems can be created virtually using real data, allowing for a thorough analysis of novel trials with realistic environments and targets.

VII. CONCLUSION

In this article, we presented a MaMIMO testbed design and implementation, which are the measurement foundation for creating massive CSI data sets. The flexible antenna deployment capabilities of the KU Leuven MaMIMO testbed allow for distinct antenna array topologies including URA, ULA, and DA. Moreover, for an automatic and accurate measurement campaign, we developed a central controller that accurately moves a user through the testing scenario while directing the BS to conduct channel measurements at the different locations, which prompts us to obtain the DDS with 252,004 location-labeled CSI samples for a grid of 5 mm in space.

For real applications, the DDS was used to generate the normalized received signal strength over the scanned area when beamforming towards a specific location. A CNN was trained using the DDS to extract location information out of CSI data. Then, the location knowledge was used to develop a location-based user scheduling technique, which was compared with SUS using the DDS. The results show that SUS outperforms the proposed methods in terms of SE, however it has a higher computational complexity. The bulk of work based around the presented data sets results in complete building blocks for joint communication and localization systems. Finally, future directions for this open data set are presented. This work shows the value of such open data sets for the scientific community.
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Achiel Colpaert [IEEE Member] obtained his BSc and MSc degrees in electrical engineering from KU Leuven, Belgium respectively in 2015 and 2017. Currently, he is working towards his Ph.D. at KU Leuven, focusing on high-throughput wireless links for UAV applications.

Sibren De Bast [IEEE Member] received a Ph.D. degree in electrical engineering from KU Leuven, Leuven, Belgium, in 2022. His current research interests include AI for communications and localization.

Robbert Beerten obtained his BSc in Engineering and his MSc in Electrical Engineering from KU Leuven in 2019 and 2021, respectively. He is currently working as a Ph.D. researcher, focusing on optimization and distributed signal processing for next-generation networks.

Andrea P. Guevara [IEEE Member] obtained her BSc in Electronics and Telecommunications at the University of Cuenca, Ecuador in 2013. In 2015, she obtained her MSc in Telecommunications and the prize for the best academic performance in Research at King’s College London, UK. In 2022, she got her Ph.D. degree at KU Leuven, her main interests are interference analysis and cooperation in MaMIMO systems.

Zhuangzhuang Cui [IEEE Member] received his Ph.D. degree from Beijing Jiaotong University (BITU), Beijing, China, in April 2022. Currently, he is a Postdoctoral Mandate (PDM) at KU Leuven, Belgium. From 2019 to 2021, he was a visiting scholar and Ph.D. student at several universities (UPM, NCSU, UCLouvain) in Spain, the USA, and Belgium. His research interests include channel modeling and non-territorial networks.

Sofie Pollin [IEEE Senior Member] received a Ph.D. degree (Hons.) from KU Leuven, in 2006. From 2006 to 2008, she continued her research on wireless communications at UC Berkeley. In 2008, she returned to IMEC to become a Principal Scientist at the Green Radio Team. She is currently a Full Professor at the Electrical Engineering Department, KU Leuven. Her research interests include networked systems that require dense, heterogeneous, battery-powered, and spectrum-constrained networks. She is a BAEF Fellow and a Marie Curie Fellow.