Evaluation of Location-aided Coordinated Beamforming by Active Inference in Realistic City Scenario

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***Abstract*—In recent years, the utilization of higher-frequency radio waves, which can carry more information, has been explored to achieve higher-capacity wireless communications for Beyond 5G/6G. Beamforming is employed to mitigate attenuation of high-frequency radio waves during propagation. It is important for the base station to quickly track the constantly changing CSI (Channel State Information) and incorporate it in beam selection to maintain stable and high throughput. To achieve this, an effective approach is to use an active inference framework that is able to balance obtaining information and actions that lead to the achievement of objectives, based on both the user's knowledge and information from the environment. In this paper, we propose a beamforming method that uses active inference based on the terminal location information obtained by PRS (Position Reference Signal) and the signal strength of the communication to infer CSI and perform appropriate beam selection. Since the transmission and reception of PRS consume communication resources, the throughput is reduced during location measurement. Therefore, our method also controls the frequency of obtaining location information within active inference. Simulations in a realistic urban environment demonstrated that utilizing location information in active inference achieves a high throughput more stably compared to scenarios without location information.**

***Index Terms*—beamforming, active inference, massive MIMO**

I. Introduction

In recent years, the utilization of higher-frequency radio waves, which can carry more information, has been explored to achieve higher-capacity wireless communications for Beyond 5G/6G [1]. However, high-frequency radio waves are subject to significant attenuation due to environmental factors such as rain and obstacles in the propagation path [2]. Accordingly, the base station coverage area becomes smaller and the frequency of terminals crossing the area increases. Therefore, maintaining stable communication quality becomes challenging.

A technology called beamforming is used to solve this problem. This is a technique in which signals are processed using Massive MIMO, a technique where a base station equipped with many antennas transmits signals in a specific direction. This approach concentrates power and mitigates the effect of radio wave attenuation during propagation [1]. To achieve this, it is important to understand information about the communication environment, such as the surrounding physical environment and the effective direction of the beam. This information is called CSI (Channel State Information). However, it is difficult to capture CSI accurately when Massive MIMO is equipped with many antennas. The challenge is how to maintain high throughput in an environment where accurate CSI cannot be obtained and is constantly changing [1]. In addition, base stations need to coordinate with each other to mitigate the negative effects of inter-base station interference to maintain stable communication quality over a wide area [3].

An effective approach to solving this problem is for the base station to actively obtain information to understand environmental changes and then select an appropriate beam. In addition, by sharing information among base stations, it is possible to make decisions that take into account the presence of other base stations. To achieve these goals, an active inference framework can be used.

Active inference is a theory proposed in neuroscience, in which an organism's brain obtains information from its environment through its own actions and makes decisions to change its environment to achieve its goals [4]. This decision-making is formulated as the minimization of the expected free energy [5]. The expected free energy decreases when one obtains more information or gets closer to achieving one's goal. Therefore, minimizing expected free energy can be considered a model for deciding to acquire information in uncertain environments and for selecting actions to achieve goals when the environment is well understood. In fact, it is considered effective to use the active inference framework for beamforming [6].

Since beamforming is a technique that transmits radio waves in the direction of the terminal, the result is considered to be strongly dependent on the terminal's location information. In [7], an efficient beamforming method has been proposed by creating a database linking beamforming results and location information. In this paper, we propose a more stable beamforming method based on the active inference that complements CSI with high uncertainty by using location information obtained for the active inference. While the method in [7] creates a database to map location information to beam selection, our method synthesizes the obtained information to make inferences about the environment and maps the results to beam selection. Since it does not rely on a database, our method can adapt to a highly volatile environment. We use PRS (Position Reference Signal) [8] to obtain the terminal's location information. Unlike GPS and other external sensing methods that are difficult to use indoors, PRS can be used regardless of location because this method is completed between base stations. On the other hand, since PRS consumes communication resources, the use of PRS incurs overhead. Therefore, it is desirable to minimize the frequency of obtaining location information as much as possible. For this reason, the base station obtains location information at a certain frequency, and the frequency is controlled by the active inference.

In general, communication environments are complex due to buildings and other obstacles, and it is important to evaluate the performance in such environments. Therefore, in this paper, we evaluate the proposed method using DeepMIMO [9], [10] on a dataset based on the actual New York City area. By doing so, we demonstrate the effectiveness of the proposed method in a realistic and complex environment.

This paper is organized as follows. Section 2 reviews prior research in areas such as beamforming and active inference. Section 3 details the proposed methodology. Section 4 describes the evaluation setup and presents the experimental results.

II. Related Work

A. Active Inference

We use active inference in the proposed method. Active inference is a concept proposed in the free energy principle, a theory that uniformly explains the functions of the brain. Active inference is a model of the interaction between an environment and an organism, where the organism obtains information from the environment through its actions, infers the state of the environment, and influences the environment through its actions to create conditions favorable to itself [4], [5], [11].

According to active inference, the brain performs two functions: inferring the state of the environment and deciding on actions towards the environment. Firstly, regarding the former, the brain updates its knowledge of the environment through Bayesian inference based on the information obtained from the environment. In this case, the brain tries to minimize variational free energy, which is the upper bound of the surprise, and understands the environment so that the information becomes less surprising to the brain [4].

Secondly, regarding the latter, we categorize the benefits of actions into two types: informational gain and practical value of approaching brain goals as preference. The objective function that considers these two benefits is the expected free energy (EFE) G_π. Let s denote a state of the environment, o denote an observation, π denote a policy, C denote a preference, p denote a probability distribution of the environment, and q denote the brain's inferred probability distribution of p, then EFE G_π is defined as follows [5]:

$$\begin{aligned} G_\pi &= \mathrm{E}_{q(o,s|\pi)} \left[\ln q(s \mid \pi) - \ln p(o, s \mid \pi)\right] &(1)\\ &\simeq -\mathrm{E}_{q(o,s|\pi)} \left[\ln q(s \mid o, \pi) - \ln q(s \mid \pi)\right] \\ &\quad - \mathrm{E}_{q(o|\pi)} \left[\ln p(o \mid C)\right]. &(2)\end{aligned}$$

EFE is defined by Equation (1), but since the brain cannot know the probability distribution p of the environment, we use its approximation, Equation (2). The first term of this equation is informational gain, and the second term is practical value.

B. Beamforming using Massive MIMO

In [1], beamforming techniques using Massive MIMO in millimeter-wave communications are described.

Transmitted signals undergo various types of losses during propagation. Massive MIMO, a technology that employs numerous antennas, performs signal processing in advance to mitigate these effects. Beamforming is a technique that mitigates these losses by concentrating power in a specific direction.

In order for beamforming to achieve stable and high throughput, it is important to accurately estimate the CSI. However, Massive MIMO generally has a very large number of antennas, which makes CSI estimation complex and difficult. For this reason, various methods have been considered, such as the CSI estimation method using deep learning [12] and the beamforming method, which does not explicitly estimate the CSI but learns the appropriate beam through exploration, as reported in this paper.

The performance of beamforming is considered to be highly dependent on geometrical information because beamforming is a technique for transmitting radio waves towards terminals. Therefore, the use of location information of the terminal is considered to be useful for improving it. In [7], a method for Beamforming using location information is proposed. This method performs efficient beamforming by creating a database that includes location information. However, it requires a stationary communication environment. On the other hand, our method can perform efficiently without the requirement. Beamforming based on active inference attempts to collect information about the significantly changed environment.

In [6], the effectiveness of beamforming with ISAC (Integrated Sensing and Communication) as an input to active inference has been demonstrated.

In this paper, we propose a beamforming method using PRS (Position Reference Signal) as an input for active inference. Unlike GPS, PRS can be used indoors or in any other location because location information can be measured only at the base station, albeit with the use of communication resources [8]. While ISAC obtains location information via radar and requires additional processing to identify the terminal from the acquired data, PRS directly provides the terminal's location information.

There is a trade-off in using PRS. If the frequency of PRS usage is high, a lot of communication resources are consumed. If not, the accuracy of location information decreases due to delayed updates. In our method, the base station obtains location information at a certain frequency, and the frequency is controlled by active inference to manage the trade-off.

C. Coordinated Beamforming

Transmitted radio waves from each base station interfere with each other before reaching the terminal in a communication environment with multiple base stations. This causes weakening of the radio waves and throughput degradation. To prevent this, research is being conducted on how to coordinate base stations. In [3], various coordination policies are mentioned. For example, CS/CB (Coordinated scheduling and coordinated beamforming) is a policy of coordination to suppress the effects of interference, and JT (Joint Transmission) is a policy of coordination to strengthen each other's signals by using interference.

In this paper, each base station shares its inference result at regular intervals so that it can perform beamforming while referring to the inferences of neighboring base stations. This approach allows each base station to choose actions that take into account the inferences of other base stations and to coordinate with a policy that is appropriate for each environment.

III. Method

A. Overview of the Method

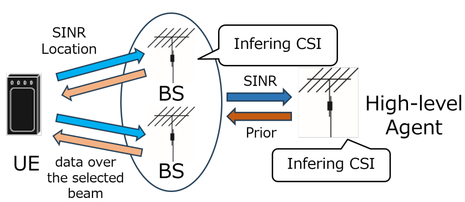

Fig. 1. System overview (using icons in [13])

In our method, both the base station and the high-level agent each perform active inference and control the behavior of the base station according to the results. Figure 1 shows the system overview. The base station control procedure is as follows:

1) The base station measures throughput from the terminal at that time. When it is time to update location information, it also obtains location information of the terminal.
2) The base station infers CSI based on the obtained information.
3) The base station decides the beam shape and the frequency of obtaining location information.

In addition, the high-level agent regularly collects inferred CSI from base stations and infers CSI based on them. The result of this inference is distributed to base stations.

B. Active Inference by the Base Station

The base station performs active inference under the following settings.

a) Internal state: Assume that CSI is finite and discrete, and each internal state is denoted by s_i $(i = 0, 1, \cdots, N_s)$, where N_s is the number of internal states.

b) Observation: The base station obtains a tuple of observations $o = (\text{SINR}, \text{location information of the terminal})$.

SINR (Signal-to-Interference-plus-Noise Ratio)
SINR is the ratio of signal power to noise, taking inter-station interference into account. The following Equation (3) holds between SINR and data rate R [1]:

$$R = B \log_2(1 + \text{SINR}), \tag{3}$$

where B is bandwidth. When at least one of the base stations obtains location information, a communication resource is used. In this paper, we assume that one of the 14 symbols of an OFDM subcarrier is allocated for PRS. In other words, we assume that R is multiplied by $13/14$ when a base station obtains location information.
To incorporate this adjustment into SINR, convert SINR to R using Equation (3), scale it by 13/14, and recalculate SINR using Equation (3). Let SINR' be the SINR with this correction applied. Then,

$$\text{SINR}' = 2^{R'_b} - 1,\ R'_b = r \log_2(1 + \text{SINR}) \tag{4}$$

$$r = \begin{cases} \dfrac{13}{14} & \text{(when obtaining location information)} \\ 1 & \text{(otherwise)} \end{cases}$$

The base station obtains the discretized SINR' in dB.

Location information
The base station obtains the distance and the azimuth of the terminal relative to itself. These values are input into the base station after being discretized. If the base station obtains location information, it obtains location information at that time; otherwise, it continues to obtain the last obtained location information.

c) Action: The base station decides a tuple of actions $a = (\text{subsequent beam}, \text{frequency of obtaining location information})$.

Beam shape The base station decides the code index q_1 for the shape and the power index q_2 of the subsequent beam. The base station transforms the data stream $\boldsymbol{s}$ based on this decision before transmitting it. The received signal $\boldsymbol{y}$ can be formulated as follows [1]:

$$\boldsymbol{y} = H\sqrt{p_{q_2}} W^{q_1} \boldsymbol{s} + \boldsymbol{n}. \tag{5}$$

where H is a channel matrix and $\boldsymbol{n}$ denotes noise.
Regarding code, the base station selects a code from the following codebook W^{q_1} as stated in [3]:

$$W_i^{q_1} = \frac{1}{\sqrt{N}} \exp\left(j\frac{2\pi i q_1}{N}\right),\ (i \in \mathbb{Z}, 1 \le i \le N) \tag{6}$$

where $q_1 \in \mathbb{Z},\ 0 \le q_1 < N$, and N is the number of antennas of a base station. The base station selects a code by setting the value of q_1. Regarding the power, the base station selects an index of the power q_2 from predefined options.

Frequency of obtaining location information The base station selects a frequency from predefined options.

d) Preferences: The preference is a representation of the observations that are preferred by an active inference agent. The base station sets its preference proportional to the discrete value of $\mathrm{SINR}'(\mathrm{dB})$ to maximize the SINR sent by the terminal.

C. Active Inference by the High-level Agent

The high-level agent performs active inference to achieve coordinated beamforming under the following settings.

a) Observation: The agent obtains SINR as feedback from the terminal and CSI inferred by base stations. Regarding SINR, the agent does not correct SINR by acquiring location information, unlike base stations, which do. In other words, the agent always computes SINR' assuming $r = 1$ in Equation (4). This is because the agent does not know whether the base station has obtained location information and thus cannot detect any changes caused by it.

b) Coordination: The agent infers CSI based on the CSI inferred by the base stations and the SINR, and then shares the resulting inference with the base stations. The base stations set it as their own prior belief, which is the basis of their inference process. In this way, the base station can consider neighboring base stations in their inferences and perform coordinated beamforming.

The internal state and preferences are the same as for the base station, and no actions are taken.

IV. Evaluate

A. Environment

1) DeepMIMO: We perform simulations and evaluate performance using DeepMIMO [9], [10], [14]. DeepMIMO is a tool that can generate channel matrix datasets by performing ray-tracing simulations for pre-prepared scenarios. In this paper, we use a scenario based on the New York City environment (Figure 2).

Fig. 2. City_0_NewYork Scenario (Source: [9], with red lines added by the authors, created using Graphing Calculator in Desmos [15])

The main parameters in DeepMIMO are shown in Table I. Due to limitations of the dataset, the channel matrices that can be obtained are limited to those at the grid intersections predefined in the scenario, thus DeepMIMO cannot generate the channel matrix at every location. Therefore, in this simulation, the base station observes the weighted average SINR of neighboring SINRs.

TABLE I
MAIN PARAMETERS IN DEEPMIMO

parameter	value
radio frequency	3.5 GHz
antenna spacing	half-wavelength
bandwidth	0.05 GHz
total number of OFDM subcarriers	512
number of subcarriers under consideration	1

We denote the SINR at each of the four intersection points p_i $(0 \leq i \leq 3)$ in the neighborhood of the terminal by SINR_i and the distance between the terminal and the intersection point p_i by d_i. Then, the Average SINR is defined as follows:

$$\text{Average SINR} = \sum_{i=0}^{3} w_i \cdot \mathrm{SINR}_i, \quad w_i = \frac{1/d_i}{\sum_{j=0}^{3} 1/d_i}. \tag{7}$$

2) Base Station: The base station is a ULA (Uniform Linear Array) with 8 isotropic antennas aligned parallel to the ground. The base station location is indicated by the blue circle in Figure 2. Next, the parameters of active inference performed by the base station are described.

- The base station performs active inference every second.
- The number of internal states of the base station is 50.
- The power options are $-70\,\mathrm{dBm}$, $-35\,\mathrm{dBm}$, $0\,\mathrm{dBm}$, $35\,\mathrm{dBm}$, and $70\,\mathrm{dBm}$.
- The available options for the frequency of obtaining local information are every 10, 20, and 40 inferences.
- The discretization of the observation is performed at equal intervals according to Table II. If the observation exceeds the discretization range, the observation is discretized as the maximum or minimum value of the range.

TABLE II
THE DISCRETIZATION OF THE OBSERVATION

	range	levels
SINR	$[-10\,\mathrm{dBm}, 90\,\mathrm{dBm}]$	10
distance	$[0\,\mathrm{m}, 100\,\mathrm{m}]$	4
azimuth	$[0\,\mathrm{rad}, 2\pi\,\mathrm{rad}]$	8

Lastly, we describe the parameters of the high-level agent. Coordination among base stations is performed every 5 inferences, and the high-level agent has 10 internal states.

3) Terminal: The terminal is assumed to be a device owned by a pedestrian. It is equipped with an antenna, and moves at a constant speed of 1.75 m/s. It moves straight until it reaches an intersection. When it arrives at the intersection, it randomly changes direction. The terminal's path follows the red line in Figure 2. If it reaches the end of the red line, it turns around. Note that all the paths of the terminals are within the LoS (line-of-sight) range of at least one base station.

We perform simulations of the following two settings, and compare the SINR'.

Proposed method: Active inference with the terminal location information (Section 3)

Comparative method: Active inference without the terminal location information

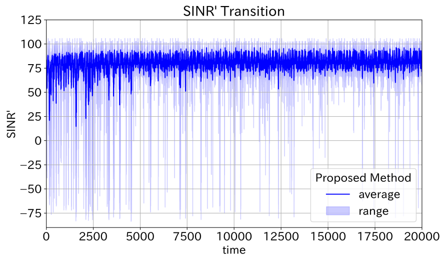

Fig. 3. Proposed Method: SINR$'$ Transitions at Various seeds

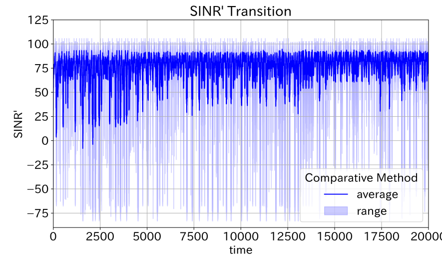

Fig. 4. Comparative Method: SINR$'$ Transitions at Various seeds

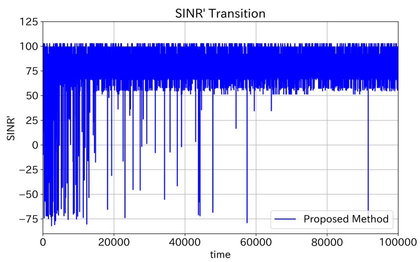

Fig. 5. Proposed method: SINR$'$ Transition

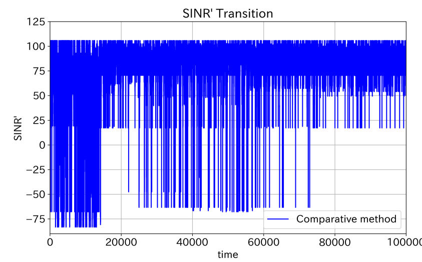

Fig. 6. Comparative method: SINR$'$ Transition

B. Result

First, simulations of each method were performed with 11 different seed values, and the evolution of the average SINR over time for the seed values at each time point is summarized in Figures 3 and 4. The SINR for both methods is unstable immediately after the start of the simulation due to the lack of knowledge about the environment. As learning progresses, the SINR becomes more stable. Comparing the two methods, the proposed method has a more stable average value, indicating that the proposed method has a higher probability of succeeding in providing stable communication quality. In addition, the proposed method achieves stable SINR for most of the seed values from the initial stage.

Then, for each of the methods, a long-time simulation was performed to compare the improvement in the seed where SINR stability was not achieved by time = 20000 (Figures 5,6). These figures show that the comparison method frequently drops the SINR to 20 dB over a long period of time, while the proposed method decreases the frequency of SINR drops over time, and finally stabilizes the SINR in the range of 60 dB to 100 dB. In the proposed method, the drop in SINR is observed even after stabilization, but this is considered to be due to the fact that active inference involves probabilistic behavior.

To analyze the decrease in SINR more closely, we created box plots for each 5000 time units (Figures 7 and 8). Figure 8 shows that the statistical change in SINR becomes smaller over time for the comparative method, while outliers continue to appear. On the other hand, in Figure 7, outliers hardly appear in the final stage for the proposed method. This suggests that the use of location information for active inference leads to a better solution that can suppress the drop in SINR and improve stability.

Finally, Figure 9 shows when the base station obtains location information at the end of the simulation in the proposed method, and Figure 10 shows the coordinate transition of the terminal. The base station numbers in Figure 9 correspond to those in Figure 2.

Assuming that base stations can determine terminal positions by transmitting PRS independently [16], this method reduces the number of base stations transmitting PRS, thereby decreasing the communication resources used for PRS across the entire network. Even when combining multiple base stations for position measurement, not all base stations are employed, so a reduction in communication resources can be expected. Under this assumption, 9 shows that BS 2 can reduce its PRS exchange frequency to 77.0% and that of BS 3 to 27.0% compared to continuously exchanging PRS at the maximum frequency. Thus, while PRS-based positioning involves a trade-off between information accuracy and resource cost, this method allows these factors to be balanced according to the situation.

V. Conclusion

In this paper, we propose a beamforming method that utilizes location information for active inference, and we evaluate its effectiveness in a realistic city scenario through simulations. We conclude that in a complex environment with a mobile terminal, active inference using SINR and location information from base stations can provide more stable communication quality than active inference using SINR alone.

Since this method requires additional communication resources to obtain location information, we designed the method to control the location-update frequency in an integrated manner to avoid excessive location acquisition. We also show that this control can enable role division so no base station obtains location information at an excessive frequency, thereby enabling efficient use of communication resources.

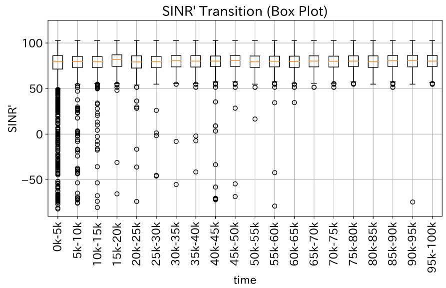

Fig. 7. Proposed Method: SINR′ box plots

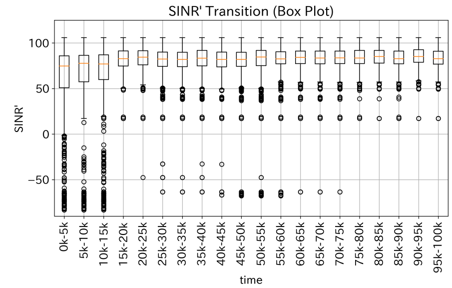

Fig. 8. Comparative Method: SINR′ box plots

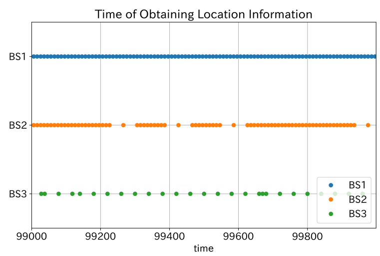

Fig. 9. Proposed Method: time of obtaining location

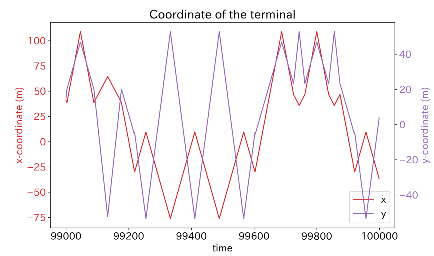

Fig. 10. Transition of the coordinate of the terminal

The environment used for evaluation in this paper does not fully reflect real-world conditions, since environmental changes are limited to terminal movement. Therefore, it will be important to validate the method under diverse conditions, such as weather variations and moving obstacles. In addition, although this method was evaluated for a single terminal, real-world environments typically include multiple terminals. Therefore, it is necessary to extend the method to multiple terminals. In this case, it is essential to consider fairness across terminals, which was not a factor in the single-terminal scenario, and refine the design of active inference.

In future work, we will explore a system in which the high-level agent supports the allocation of communication resources to users by using active inference. The high-level agent can obtain information about a wide area including two or more cell-coverage areas. Using this information, the system can consider fairness across terminals.

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