

# Analysis of Mobility Entropy for Representation of Human Movement in Digital

MinHo Han \*, Keun-Woo Lim\*\*, Young-Bae Ko\*

\* Dept. AI Convergence Network, Ajou University, Suwon, South Korea

\*\* Telecom Paris, Institut Polytechnique de Paris, Palaiseau, France

vosej2414@ajou.ac.kr , keunwoo.lim@telecom-paris.fr, youngko@ajou.ac.kr

**Abstract**—This work analyzes the effect of mobility entropy in real-time representation of human positioning in digital twin applications. Real-time representation of positioning data is challenging due to the energy constraints of IoT devices, inducing a tradeoff between representation accuracy in digital twin applications and energy efficiency in real-world IoT devices. We consider the utilization of mobility entropy, which reflects the dynamics of a movement, to leverage the tradeoff for more efficient management of both IoT and digital twins. Our preliminary analysis shows that our proposed calculation of mobility entropy can accurately capture mobility characteristics and suggests that this value can be used future methods of enhancing and optimizing accuracy and energy efficiency.

**Keywords**— Digital twins, Mobility Entropy, Ultra wide-band

## I. INTRODUCTION

Digital Twin (DT) technology has revolutionized how we monitor, simulate, and optimize real-world systems by creating virtual replicas that reflect physical entities in real time. The integration of Internet of Things (IoT) devices in Digital Twin frameworks has enabled continuous data collection and interaction between the physical and virtual realms. This connectivity is crucial for applications in smart factories, healthcare, and urban planning, where precise localization and tracking of mobile entities are vital.

However, the continuous influx of data required for real-time representation poses significant challenges, particularly for mobile IoT devices with limited energy resources. One notable example is in the scope of real-time indoor positioning of humans and mobile devices. This is because accurate real-time representation of a mobile entity requires high sampling rate of localization sensors to track every movement, which in turn induces higher energy consumption. While technologies such as Ultra-wideband (UWB) has emerged as a preferred solution for high-precision indoor localization, offering low-power communication, there remains a critical need to optimize energy consumption without compromising the accuracy of digital representation.

In this context, understanding the movement patterns of mobile entities, particularly humans, becomes crucial. Human movement is often irregular and unpredictable, resembling Brownian motion—a random, continuous path similar to the physical process observed in particles suspended in fluid [1]. This randomness in movement patterns requires continuous and periodic influx of positioning data in rapid intervals to

accurately represent the dynamicness of the movement. On the other hand, if the movement is predictable (for example moving in a straight line), the sampling rate of positioning can be reduced to save energy. By understanding the dynamicness of human movement based on these mobility models such as Brownian motion, we can better predict and adapt to these complexities in real-time localization systems.

This study aims to explore the relationship between energy efficiency and localization accuracy in real-time Digital Twin applications, specifically by utilization of Brownian motion. We investigate how different sampling rates affect the accuracy of UWB-based localization, but even more importantly, how the dynamicness of a movement which we define as mobility entropy [2], impacts accuracy and energy efficiency in a different behavior. Mobility Entropy (ME) is a metric developed to quantify human indoor mobility by measuring the variability and unpredictability of movement patterns. The concept of ME, for example, was applied by Chernbumroong, et. al., [2], in an Ambient Intelligent (AmI) environment to predict indoor mobility patterns. ME has since proven to be an effective indicator for detecting changes in mobility, offering significant potential for personalized care in smart environments.

From the results that we obtain, we suggest in our future work that sampling rates in UWB-based localization systems can be optimized, potentially by using our mobility entropy. By leveraging this model, we can dynamically adjust the sampling frequency based on the unpredictability of movement. This, in this end, demonstrates that it can significantly extend the operational life of IoT devices while maintaining high levels of accuracy in the digital representation of mobile entities.

## II. MODELING OF MOBILITY ENTROPY

### A. Brownian model

We model the movement of agents using stochastic processes to better capture the unpredictability and complexity of human motion within the given environment. This approach accounts for the random fluctuations in velocity due to a frictional force and a stochastic driving force modeled as Gaussian white noise. The differential equations governing this motion are defined as follows:

$$\mathbf{v} = \frac{d\mathbf{r}}{dt} \quad (1)$$



Figure 1. Trajectory of Moving Tag

$$\frac{dr}{dt} = -\gamma v + \sqrt{2\epsilon}\xi(t) \quad (2)$$

Where  $v$  represents the velocity,  $\gamma$  is a friction coefficient,  $\epsilon$  controls the intensity of the noise, and  $\xi(t)$  is a Gaussian white noise function. These parameters are carefully selected to simulate realistic human motion patterns in a controlled environment, following the methodology [3] and adapted for our specific application [1].

### B. Mobility entropy calculation

Mobility entropy (ME) is a measure of the randomness or unpredictability in the movement of an entity within a defined space, calculated to understand the variability in movement patterns. To compute ME, the velocity at each second is analyzed to determine the range of speeds, specifically by calculating the ( $v_{range} = \text{maximum} - \text{minimum}$ ) speeds within each time window. These values are essential because the range between them reflects the variability in speed during that period.

The second component of mobility entropy is related to the variability in the tag's movement direction, quantified by the range of angle changes observed during each time interval:  $\Delta\theta_i = \text{maximum}\Delta\theta_i - \text{minimum}\Delta\theta_i$ , where  $\Delta\theta_i$  denotes the change in angle within the  $i$ -th time interval. This measure captures the extent of directional changes, with larger ranges suggesting more erratic or complex movements, which contribute to higher mobility entropy. The overall mobility entropy for each interval is then calculated using a modified Shannon entropy formula, which incorporates both the normalized velocity range and the normalized angle range:

$$ME_i = -(\frac{v_{range_i}}{v_{max}} \cdot \log(\frac{v_{range_i}}{v_{max}}) + \frac{\Delta\theta_{ii}}{\Delta\theta_{max}} \cdot \log(\frac{\Delta\theta_{ii}}{\Delta\theta_{max}})) \quad (3)$$

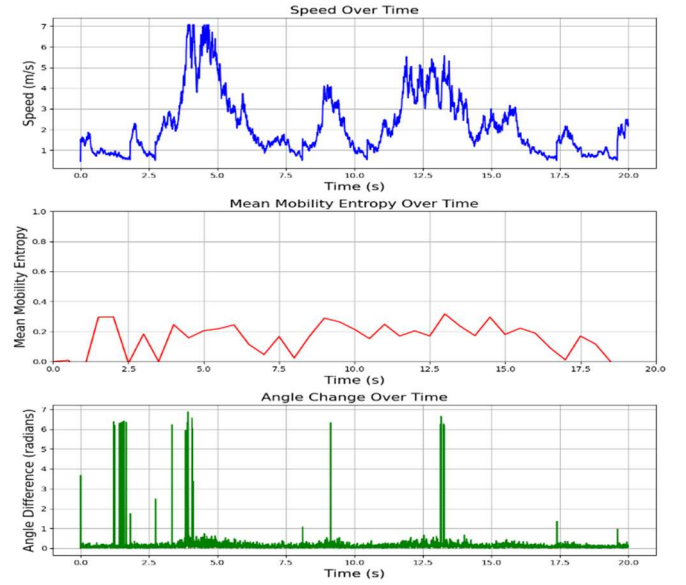


Figure 2. Speed, Angle, and Mobility Entropy changes in time window

The approach of calculating mobility entropy by first determining the maximum and minimum speeds and angles is valid because it captures the variability or fluctuation in speed, which is a key aspect of randomness in movement. High variability suggests more randomness, while low variability indicates more consistent movement. By focusing on this range, we capture the most significant fluctuations in speed, which are directly related to the entropy of the system. The logarithmic component in the entropy formula ensures that the entropy reflects not just the presence of variability, but also its degree—larger variations contribute more to the entropy.

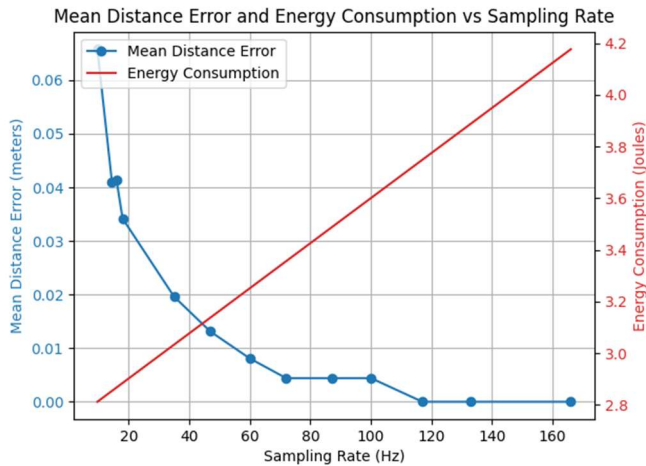
## III. RESULTS

The simulation of human movement within a Digital Twin framework was conducted using MATLAB, a versatile tool for mathematical computation and simulation. In this analysis, we examined the relationship between sampling rate, speed, angle change, and mobility entropy and their combined impact on the mean distance error and energy consumption in a tracking system. The results offer insights into the dynamic interplay of these factors, particularly at varying sampling rates.

As observed in Figure 1, indoor positioning of mobile tag is conducted in a 10m by 10m room, with four anchors located at the very end of the corners of the room. The trajectory of the movement of moving tag is simulated through Brownian motion, at the highest sampling rate (166 Hz) serving as ground truth. Figure 2 offers additional context by demonstrating the speed, mobility entropy, and angle change over time. As shown in Figure 2, periods of high speed are correlated with sharp angle changes, which in turn cause spikes in mobility entropy. These spikes in mobility entropy are reflective of the system's struggle to maintain accurate tracking under conditions of rapid movement and directional change. The trajectory in Figure 1 reflects these challenges, with more erratic paths observed

**TABLE 1.** THE ERROR RATE ON THE VARIOUS MOBILITY ENTROPY DISTRIBUTIONS ON THE DIFFERENT SAMPLING RATES

| Communication Rate         | 9.67Hz | 18Hz | 35Hz | 47Hz  | 60Hz  | 72Hz  | 87Hz  | 100Hz | 133Hz |
|----------------------------|--------|------|------|-------|-------|-------|-------|-------|-------|
| Low Entropy Value(0.3)     | 1.08m  | 1.3m | 1.3m | 0.99m | 0.96m | 0.7m  | 0.7m  | 0.47m | 0.27m |
| Medium Entropy Value(0.52) | 1m     | 1.5m | 1.5m | 1.3m  | 1m    | 0.76m | 0.71m | 0.65m | 0.3m  |
| High Entropy Value(0.74)   | 2.75m  | 2.8m | 2.6m | 2.6m  | 2.37m | 1.64m | 1.9m  | 1.4m  | 0.98m |

**Figure 3.** Mean Distance Error and Energy Consumption Rate based on Different Sampling Rates

during high-speed segments. Together, these figures demonstrate that the combination of high speed and frequent angle changes creates conditions that are particularly challenging for lower sampling rates, leading to higher errors and greater variability in tracking accuracy.

Table I presents the error rates corresponding to different sampling rates under varying mobility entropy conditions—low (0.3), medium (0.52), and high (0.74). The data demonstrates that as mobility entropy increases, the error rate tends to rise across all sampling rates, indicating the need for higher sampling rates to maintain accuracy in more dynamic environments. For instance, with low entropy (0.3) and medium entropy (0.52), a sampling rate of 72 Hz or higher provides reasonably low error rates, making it an energy-efficient choice. In contrast, at high entropy (0.74), significantly higher sampling rates are required to keep error rates manageable, with 133 Hz showing the best performance. This pattern suggests that our proposed measure of mobility entropy has high correlation to the accuracy of real-time position representation, and that it can be effectively utilized to dynamically adjust sampling rates. This in turn can be used to optimize the trade-off between energy consumption and positional accuracy. Note that the mean entropy presented in Figure 3 averages these variations, providing a general view rather than capturing the specific error rates at distinct time intervals.

Figure 3 further elaborates on this relationship by plotting the mean distance error and energy consumption against the

sampling rate. Here, we observe that as the sampling rate increases, the mean distance error decreases, which is consistent with the observations from Figure 1. However, this reduction in error comes at the cost of increased energy consumption, which is depicted in the figure. The linear increase in energy consumption with sampling rate underscores the trade-off between accuracy and energy efficiency. Interestingly, there is a sharp drop in mean distance error as the sampling rate increases from 9.67 Hz to 35 Hz, after which the error continues to decrease more gradually. This suggests that there is a threshold sampling rate, beyond which further increases yield diminishing returns in terms of error reduction.

#### IV. CONCLUSION

The concept of mobility entropy provides a valuable framework for understanding the performance of positioning representation in Digital Twins. Our proposed method of calculating mobility entropy through Brownian motion shows that 1) It is possible to detect moments of higher speed and more angular movements, and 2) mobility entropy has high correlation with accuracy determined by sampling rate of positioning information. By leveraging our proposed mobility entropy, it is possible to dynamically adjust sampling rates to balance accuracy of real-time representation in digital twin applications, while increasing energy efficiency in real-world IoT devices. Our future research will apply mobility entropy as a decision making tool to control the sampling rate of UWB devices. Firstly, we can apply machine learning to receive mobility entropy as an input and calculate the required sampling rate, leveraging energy and accuracy. Furthermore, we will consider theoretical evaluation and optimization of these two parameters in the real-time representation scenario. Finally, we will consider applying our mobility entropy and compare with real-world experimentation using actual UWB devices for indoor positioning.

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