The Target Tracking in Mobile Sensor Networks

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***Abstract*—*Target Tracking* is an important problem in sensor networks, where it dictates how accurate a targets position can be measured. In response to the recent surge of interest in mobile sensor applications, this paper studies the target tracking problem in a mobile sensor network (MSN), where it is believed that mobility can be exploited to improve the tracking resolution. This problem becomes particularly challenging given the mobility of both sensors and targets, in which the trajectories of sensors and targets need to be captured. We derive the inherent relationship between the tracking resolution and a set of crucial system parameters including sensor density, sensing range, sensor and target mobility. We investigate the correlations and sensitivity from a set of system parameters and we derive the minimum number of mobile sensors that are required to maintain the resolution for target tracking in an MSN. The simulation results demonstrate that the tracking performance can be improved by an order of magnitude with the same number of sensors when compared with that of the static sensor environment.**

I. Introduction

The development of sensor network technology has enabled the possibility of target detection and tracking in a large-scale environment. There has been an increased interest in the deployment of mobile sensors for target tracking, partly motivated by the demand of habitat monitoring and illegal hunting tracking for rare wild animals [1].

In this paper, we are primarily interested in target tracking by considering both moving targets and mobile sensors as shown in Figure 1. Specifically, we are interested in the spatial resolution for localizing a target's trajectory. The spatial resolution refers to how accurate a target's position can be measured by sensors, and defined as the worst-case deviation between the estimated and the actual paths in wireless sensor networks [2]. Our main objectives are to establish the theoretical framework for target tracking in mobile sensor networks, and quantitatively demonstrate how the mobility can be exploited to improve the tracking performance.

Given an initial sensor deployment over a region and a sensor mobility pattern, targets are assumed to cross from one boundary of the region to another. We define the spatial resolution as the deviation between the estimated and the actual target traveling path, which can also be explained as the distance that a target is not covered by any mobile sensors. Given the mobility of both targets and sensors mobility, it is particularly challenging to model such a stochastic problem for multiple moving objects. Furthermore, we are also interested in determining the minimum number of mobile sensors that needs to be deployed in order to provide the spatial resolution in mobile sensor networks. It turns out that our problem is very similar to the collision problem in classical kinetic theory of gas molecules in physics, which allows us to establish and derive the inherently dynamic relationship between moving targets and mobile sensors.

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The binary sensing model of tracking for wireless sensor networks has been studied in several prior works. The work in [3] showed that a network of binary sensors has geometric properties that can be used to develop a solution for tracking with binary sensors. Another work [4] also considered a binary sensing model. It employed piecewise linear path approximations computed using variants of a weighted centroid algorithm, and obtained good tracking performance if the trajectory is smooth enough. A follow-up work explored fundamental performance limits of tracking a target in a two-dimensional field of binary proximity sensors, and designed algorithms that attained those limits in [5]. Prior works in stationary wireless sensor networks have studied the fundamental limits of tracking performance in term of spatial resolution.

Our focus in this paper is completely different from all prior works. There are two distinctive features of our work: 1) we try to identify and characterize the dynamic aspects of the target tracking that depend on both sensor and target mobility; 2) we consider tracking performance metrics: spatial resolution in a mobile sensor network. By leveraging the kinetic theory from physics, we model the dynamic problem, and examine its sensitivity under different network parameters and configurations. To the best of our knowledge, we believe this is a completely new study of target tracking in mobile sensor networks.

The rest of this paper is organized as follows. Section II describes the network and mobility model, as well as defining the target tracking problem in a mobile sensor network. Section III formulates the target tracking problem. Section IV examines the tracking performance sensitivity under different network parameters and configurations, and finally Section V concludes the paper.

II. Network and Mobility Model

We consider a mobile sensor network (MSN) to consist of $N(A)$ mobile sensors initially placed inside a two dimensional

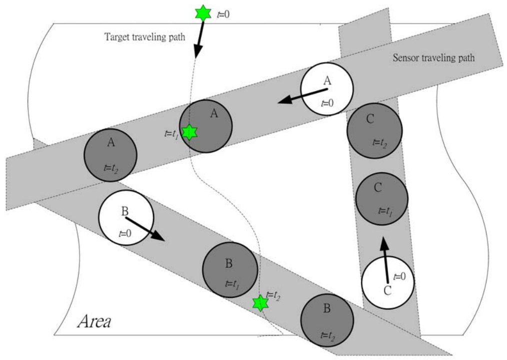

Fig. 1. Example of target tracking problem in a mobile sensor network. The difference between the intersections between sensor traveling path and target traveling path and the coverage for the target path.

geographical region A shown in Figure 1. The region can be in any convex shapes under the proposed formulation. To keep it mathematically tractable, we assume A is a rectangular region, which has four boundaries. We assume the width of the area to be W and the length to be $|A|/W$, where $|A|$ represents the area of the region. For the initial configuration (at time $t = 0$), we assume sensors are independently deployed at a random uniform distribution. Under this assumption, the sensor location can be modeled by a stationary two-dimensional Poisson process. Denote the density of the Poisson process as n_A. The number of sensors located in the region A, $N(A)$, follows a Poisson distribution of parameter $n_A \cdot |A|$. $\mathbf{Pr}(N(A) = k) = \frac{e^{-n_A|A|}(n_A|A|)^k}{k!}$, where k is a non-negative integer. We define $\mathbf{Pr}(Y)$ to be the probability that event Y occurs, and $\mathbf{Pr}(\overline{Y}) = 1 - \mathbf{Pr}(Y)$. The two-dimensional Poisson process results random uniform distribution sensor deployment at time $t = 0$. Our emphasis is on discovering the tracking performance in an MSN, and therefore we abstract away lower layer networking issues, such as the communication overhead and the network architecture of the sensors.

A. Sensing and Mobility Model

We assume that each sensor has a *sensing region* and can only sense the environment and detect events within that region. A target is any object that is subject to sensor detection and tracking as it travels in the region. It is said to be *covered* or *detected* by a sensor if it has been located inside the sensing region of the sensor. We assume the sensing region to be a disk of radius R centered at the sensor. This definition is usually referred to as a binary or disc-based sensing model [6]. In the target tracking formulation in this paper, we essentially define probabilistic tracking. Ideally, a probabilistic sensing model such as the one in [7] would be more appropriate. For simplification and mathematical tractability, we adopt the disc-based sensing model in this work.

In an MSN, depending on the mobile platform and application scenario, sensors can choose from a wide variety of mobility strategies, from passive movements to highly coordinated and complicated motion. Sensors deployed in the air, ocean or on wild animals move passively according to external forces such as air, ocean currents or wild animal movement patterns. The movement patterns are referred as the *uncontrolled* sensor mobility model; simple robots may have a limited set of mobility patterns, whereas advanced robots can navigate in a more complicated itinerary. The movement patterns are referred as the *controlled* sensor mobility model. In this work, we consider the following uncontrolled sensor mobility model. We assume that sensors move independently of each other, without any coordination between them. The movement of a sensor is characterized by its speed and direction. A sensor randomly chooses a direction $\theta \in [0, 2\pi)$ according to the distribution with probability density function $P_\Theta(\theta)$. The speed of the sensor is randomly chosen from a range $v_m \in [0, v_m^{max}]$, according to a probability density function of $P_{V_m}(v_m)$ and v_m^{max} is the maximum sensor speed. A sensor travels to the boundary of area A at a chosen speed and direction. Once the boundary is reached, the sensor bounds back, by choosing another angular direction and continues the process. We refer to the above model as the *random direction mobility model* [8].

Target movement is assumed to follow a crossing path, which is defined as a path (line segment) crossing from one boundary to another. We assume the velocity of a target is a constant v_i. As it will become clear in Section III, from our formulation of this paper, the target movement is not explicitly restricted to any specific mobility model; instead the most relevant parameter is the length of the path. For the mathematical tractability, it is assumed that the target mobility is independent of the sensor mobility. In reality, however, there could be spatial and temporal correlations on the mobility pattern, which are not captured in this formulation.

B. Tracking Measurement

We define the spatial resolution in MSNs as the average deviation between the estimated and the actual target travel paths, which is a extension of wireless sensor networks (WSNs) [2]. Under our network model, the deviation between the estimated and the actual paths can be illustrated as the distance that a target is not covered by any sensors. From Figure 2, the target is covered by sensors under the time periods (t_1 to t_2) and (t_3 to t_4), while it cannot be localized by any sensors before t_1, after t_4 and between t_2 to t_3. The average deviation can then be obtained by the average travel distance during those time periods. We then define *uncovered distances* as the travel distances of a target between successive sensor coverage. In this work, we use the average deviation instead of the maximum deviation for the study of spatial resolution in MSNs. As it becomes clear in Section III, from the proof, the probability distribution function of the deviation is an exponential function. The maximum deviation tends to infinite with certain probability, which makes the definition of spatial resolution meaningless if we directly extend the definition from WSNs.

III. Target Tracking in a Mobile Sensor Network

In this section, we formulate the target tracking problem in an MSN. The problem is similar to a problem in classical

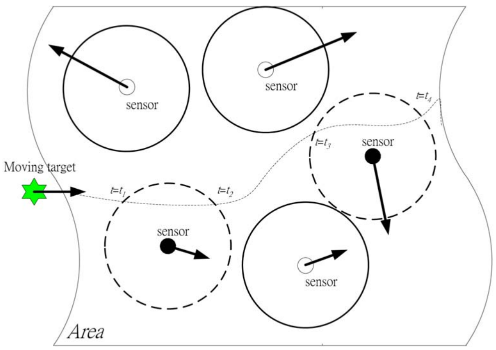

Fig. 2. The spatial resolution of a mobile sensor network.

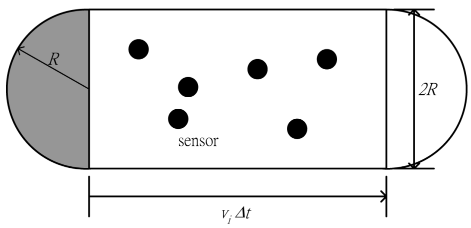

Fig. 3. An effective coverage region with sensing range R at time $t = \tau$.

kinetic theory of gas molecules in physics, specifically, the mean free path theory. For comparison, we can treat a mobile sensor as a gas molecule, and a target as an electron.

A. Spatial resolution

Our objective is to formulate the spatial resolution in MSNs. This can be achieved by modeling the average deviation between the estimated and the actual target travel paths, which is the average travel distance of a target between successive coverage by mobile sensors. We use the notation λ to represent the average travel distance of a target between successive sensor coverage. We first assume sensors are stationary and relax the assumption in the latter part of this section, then extend our formulation to consider sensor mobility. Recall that the sensing range is R, when $t = 0$, a cross section of coverage can be modeled by using a circle with the diameter $2R$. The concept of cross section is used to express the likelihood of coverage between a target and the sensors. After a period of time Δt, the circle swept out an area (shown in Figure 3) and the amount of sensor coverage can be estimated from the density of mobile sensors ($n_A = N(A)/|A|$) inside the area.

Theorem 1: The spatial resolution (average uncovered distance) in the static sensor case can be written as

$$\lambda = \frac{1}{(n_A)\cdot(2R + \pi R^2/v_i\Delta t)}, \tag{1}$$

Proof: The average uncovered distance can then be taken as the travel distance of a target divided by the number of sensor coverage, or is equal to the target speed (v_i) divided by the coverage rate (Θ_s).

$$\lambda = \frac{v_i}{\Theta_s} = \frac{v_i}{n_A \cdot S \cdot v_i} \tag{2}$$

where $S = (2R + \pi R^2/v_i\Delta t)$ is the cross section of coverage for static sensors. ∎

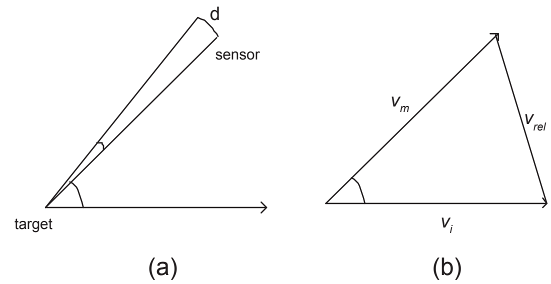

Fig. 4. (a)The speed of the moving target relative to one of mobile sensors varies only with the angle between their respective directions of motion; (b)The relative speed v_{rel}.

In order to calculate the average uncovered distance in an MSN, it is necessary to assess the average *relative velocity* of mobile sensors with respect to moving targets. The relative velocity can be expressed in terms of the targets' and sensors' velocity vectors, which are shown in Figure 4b. Different sensor mobility models can result in different relative velocity formulations. In this paper, for simplification, we use the random direction mobility model to describe mobile sensor movement. We consider the case with homogeneous velocity of mobile sensors and calculate the coverage rate. The general formulation, however, is not restricted to a specific mobility model and velocity assumption, as sensor mobility with different speed distributions $P_{V_m}(v_m)$ can also be captured under the gas kinetic framework, for example, the Maxwell-Boltzmann speed distribution shown in [9]. By recalculating the average relative speed ($\overline{v}_{rel}$) under the distribution $P_{V_m}(v_m)$ and different mobility models, we can still use the theoretical framework to compute newly uncovered distance and the new coverage rate.

Recall that the velocity vector of a target is denoted by v_i and the speed of a mobility sensor is v_m. The sensor coverage per unit time is given by $n_A \cdot S \cdot v$, and we need to replace the velocity v by the average relative speed of mobile sensors with respect to moving targets, which is denoted by $\overline{v}_{rel}$. The sensor coverage per unit time can then be written as $n_A \cdot S \cdot \overline{v}_{rel}$, where S is the cross section of coverage between the target and mobile sensors.

Theorem 2: The coverage rate can be obtained by:

$$\Theta_v = n_A \cdot S \cdot \overline{v}_{rel} \tag{3}$$

Proof: Consider a target i has a certain probability of being covered by some mobile sensors j for $j \in \forall N(A)$ a with corresponding cross section S_j and sensor density n_j. Then we have:

$$\Theta_v = \overline{v}_{rel} \cdot \sum_{j \in \forall N(A)} (n_j \cdot S_j) = n_A \cdot S \cdot \overline{v}_{rel}$$

The inverse of the coverage rate is the uncovered time duration the between successive sensor coverage. ∎

Theorem 3: With the coverage rate as $\Theta_v = n_A \cdot S \cdot \overline{v}_{rel}$, the average relative speed and the cross section of mobile sensor coverage as $S = (2R + \pi R^2/v_i\Delta t)$, we can obtain the spatial resolution (average uncovered distance) in MSNs by:

$$\lambda = \frac{v_i}{\Theta_v} = \frac{v_i}{n_A \cdot S \cdot \overline{v}_{rel}}, \tag{4}$$

B. Relative speed under the random direction mobility model

So far we have discussed the generalized formulation without a specific sensor mobility model, we now proceed to calculate the average relative speed under the random direction mobility model. However as illustrated previously, this can be applied to other mobility models. The speed of a moving target relative to mobile sensors varies only with the angle between their respective directions of movement, which is shown in Figure 4a. Since the mobile sensors move randomly in all possible directions (due to the random directional mobility model), a fraction $d\theta/2\pi$ of them move in directions that are within angle θ of the target v_i direction. Hence, for the average relative speed $\overline{v}_{rel}$, we have:

$$\overline{v}_{rel} = \frac{1}{2\pi}\int_0^{2\pi} v_{rel}\, d\theta \tag{5}$$

From Figure 4b, since $v_{rel}^2 = v_i^2 + v_m^2 - 2v_i v_m \cos\theta$ and the symmetric of θ, we can rewrite the $\overline{v}_{rel}$ as:

$$\overline{v}_{rel} = \frac{2(v_i + v_m)}{\pi} \cdot E(u), \tag{6}$$

where the incomplete elliptic integral $E(u)$ is

$$E(u) = \int_0^{\pi/2} \sqrt{1 - u\sin^2\theta}\, d\theta, \tag{7}$$

and $u = \frac{4v_i v_m}{v_i^2 + v_m^2 + 2v_i v_m}$.

Figure 5 illustrates the incomplete elliptic integral function $E(u)$ against the ratio of sensor speed to target speed ($v_m : v_i$). The result shows that the incomplete elliptic integral function is in the maximal value $E(u) = \pi/2$ at two ends ($v_m = v_i = 0$), and is in the minimal value ($E(u) = 1$) when $v_m = v_i$.

C. Distribution of spatial resolution

To explain why we use the average deviation instead of the maximum deviation for the definition of spatial resolution in MSNs, we study the probability distribution function of the uncovered distance. We consider a group of targets to be initially outside the region. Let the number originally in the group at time $t = 0$ be N_0, and at time t, N of them going without coverage by any mobile sensors. Then during the next time interval dt, the $N\Theta_v dt$ targets are covered and drop out of the group, where Θ_v denotes the coverage rate for a target with speed v_i. The change of N is $dN = -N\Theta_v dt$, which can be written as:

$$N = N_0 e^{-\Theta_v t} = N_0 e^{-\Theta_v l/v_i} \tag{8}$$

Let l be the uncovered distance for the length $v_i t$, where a target has been covered at time t. The number of targets that are covered between t and $t + dt$ and terminate a path whose length lies between l and $l + dl$ is

$$dN = -N_0 \frac{\Theta_v}{v_i} e^{-\Theta_v l/v_i} dl \tag{9}$$

Let $\varphi(l)$ be the fraction of the original N_0 targets that are still going after traveling distance l without coverage. Then let $\Psi(l)$ be the fraction of all uncovered distances of a length between l and $l + dl$. Then since $\varphi = N/N_0$ and $\Psi(l)dl = -dN/N_0$, we have

$$\varphi(l) = e^{-\Theta_v l/v_i} = e^{-l/\lambda} \tag{10}$$

$$\Psi(l) = \frac{1}{\lambda} e^{-l/\lambda} dl \tag{11}$$

where $\lambda = \frac{v_i}{\Theta_v}$. Both $\varphi(l)$ and $\Psi(l)$ are exponential functions, and λ equals the target speed divided by the coverage rate, which is the average uncovered distance. We then recalculate the expected value of l by

$$\mathbf{E}(l) = \int_{-\infty}^{\infty} l\Psi(l)dl = \lambda$$

With the uncovered distance distribution, we can also calculate the probability (percentage) of uncovered distance (x), which exceeds the average uncovered distance (λ):

$$\mathbf{Pr}(x > \lambda) = \int_x^{\infty} \Psi(l)dl = e^{-x/\lambda} \tag{12}$$

Figure 6 shows fraction of the original N_0 targets that are still going after traveling distance l without detected by sensors. Since $\mathbf{Pr}(x > \lambda)$ has a very small probability of $x \to \infty$, we use the average deviation instead of the maximum deviation for the definition of spatial resolution in MSNs.

IV. Sensitivity Analysis and Simulation Results

The formulation in the previous section mainly presents the dynamic aspects of the target tracking problem in an MSN. In this section, we investigate the correlations and sensitivity of the spatial resolution from a number of critical system parameters. Specifically, in this section we study the relationships between spatial resolution, the density of sensors and sensor mobility. We first study the correlation between the density of mobile sensors and the tracking performance. From Eqs (1) and (4), the spatial resolution is inversely proportional to the density of sensors (n_A) and the sensing range (R). The formulation is consistent with the WSN results from [2], when we consider zero mobility of sensors. From this prior work, the order of the spatial resolution bound in WSNs is also $\frac{1}{n_A \cdot R}$.

We next analyze the correlation between sensor speed and tracking performance. From Eq (4), the spatial resolution is inversely proportional to the average relative velocity ($\overline{v}_{rel}$), at the same time, the average relative velocity is affected by both the speed of the sensors and the targets (v_m and v_i). Figure 7 plots the relationships between the average uncovered distance, the sensor speed and the target speed. The average uncovered distance decreases slowly starting at $v_m \to 0$, and the negative slope of the line increases when the sensor speed is faster than the target speed.

We present numerical results verified by simulations. We develop a simulator that captures the essence aspects of the MSNs described in Section II. The simulator also provides the flexibility in selectively changing the configuration with

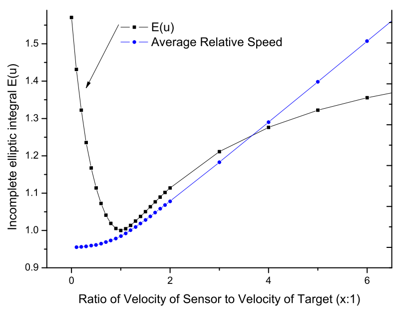

Fig. 5. Incomplete elliptic integral function and average relative speed $\overline{v}_{rel}$ against ratio of sensor speed to target speed.

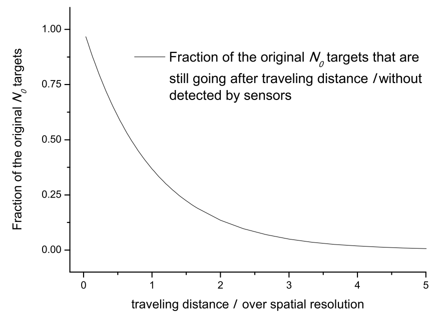

Fig. 6. Fraction of the original N_0 targets that are still going after traveling distance l without detected by sensors

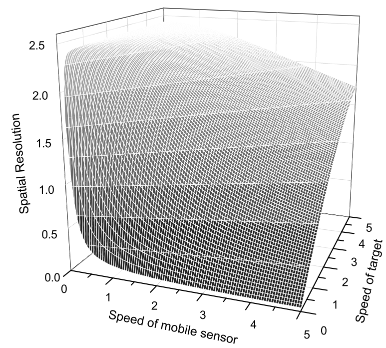

Fig. 7. The 3D plot for spatial resolution, target speed and sensor speed.

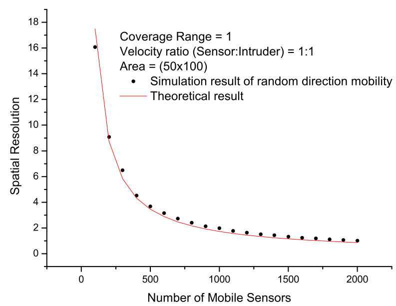

Fig. 8. The spatial resolution against density of sensor.

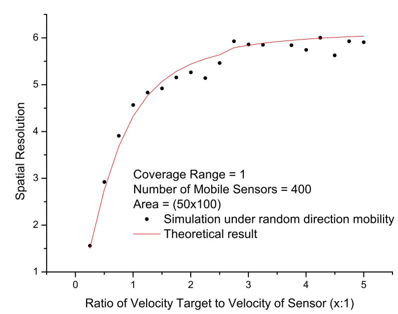

Fig. 9. The spatial resolution against ratio of target speed to sensor speed.

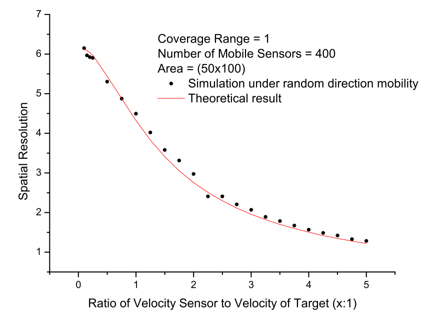

Fig. 10. The spatial resolution against ratio of sensor speed to target speed.

different parameter settings including: (i) the area size and dimension of A; (ii) the number of mobile sensors ($N(A)$); (iii) the coverage range of a sensor (R); (iv) the mobility of targets; (v) and the mobility of sensors. Unless otherwise specified, we use the following default settings: we deploy 200 mobile sensors randomly distributed in an area of size 50×100 with the coverage range of sensors $R = 1$. Figures 8, 9 and 10 illustrate the spatial resolutions against density of sensor, ratio of target speed to sensor speed, and ratio of sensor speed to target speed, respectively. The calculated spatial resolutions are also almost the same as the simulation results. The results also show that sensor mobility can be exploited to compensate for the lack of sensors and improve tracking performance.

V. Conclusions

In this paper, we have studied the target tracking problem in mobile sensor networks. Specifically, we introduce performance metrics: spatial resolution, and we investigate the resolution against moving targets. By modeling the dynamic aspects of the target tracking that depend on both sensor and target mobility, we derive the inherent relationship between the spatial resolution and a set of crucial system parameters including sensor density, sensing range, sensor and target mobility. The results demonstrated that mobility can be exploited to obtain better spatial resolution.

There are several avenues for further research on this problem: (1) to consider the detection error of mobile sensors under varying sensor speeds. This can be formulated into an optimization problem for target tracking; (2) to refine the sensor mobility model, the network model, and the communication model among sensors in order to enable effective detection and tracking. For example, a practical distributed target tracking and sensing information exchange protocol becomes an interesting future research topic when sensors are required to trace the target paths.

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