

# Improving non-line-of-sight situations in indoor positioning with ultra-wideband sensors via federated Kalman filter

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## ABSTRACT

Ultra-wideband (UWB) technology is renowned for its exceptional performance in fast data transmission and precise positioning. However, it faces sensitivity challenges when the tagged object is not in direct line of sight, resulting in position inaccuracies. Applying the federated Kalman filter (FKF), this research focuses on mitigating position deviation induced by non-line-of-sight (NLOS) scenarios in UWB technology. The utilization of the FKF in NLOS scenarios has demonstrated a noteworthy reduction in position deviation. This study uses the FKF to analyze measurements taken under line-of-sight (LOS) and NLOS conditions within indoor settings. The outcomes of this study provide a promising foundation for future research endeavors in the field of UWB technology, emphasizing the potential for improved performance and accuracy in challenging operational environments.

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## 1. INTRODUCTION

The positioning has become an increasingly important issue for humanity in recent days. Because with the developing technology, positioning has become essential in many cases and will continue to come. Because of that, people spend more and more time indoors daily. In the mornings, we are usually in an office or school environment, and in the evenings, we are often in our homes or spending time in malls or cafes. When we are sick, we go to hospitals, another indoor environment. The amount of time people spend outdoors is decreasing, meaning location tracking needs to be improved to direct or track people in these environments. Location tracking is based on estimating the location using at least three readers and one tag, using the distance between each reader and the tag. However, in real life, the distances between the tag and the readers due to the presence of objects need to be formed correctly. These situations where the reader and the tag cannot see each other directly are called non-line of sight (NLOS). In these cases, ultra-wideband (UWB) technology has resorted to two different ways, such as improving the locations with algorithms to increase the accuracy of the location and creating a location accordingly by understanding whether there is NLOS or not.

Much research has been done to improve NLOS conditions. Some of this research is on UWB technology. The methods used to strengthen NLOS conditions can take different forms. Improvements have been made by replacing the device physically, making hardware changes, or applying filters. Although the number of previous literature studies in this area is minimal, it can be seen that NLOS problems are divided into two groups: NLOS identification and NLOS mitigation [1].

Improving NLOS conditions means more accurately predicting the location of people in confined spaces. This is very important for the modern world because humanity is spending more time indoors than ever before, which means that the times when we need directions in shopping malls are increasing. In addition, the increase in consumption has caused the products to be followed from the production line in closed areas to the customer's home. Therefore, improving the position estimation in NLOS situations is very important.

This study examined NLOS situations in UWB with the federated Kalman filter (FKF). In the second part, methods of improving NLOS states are mentioned. In the third section, the study focuses on utilizing the FKF structure. In the next section, we will examine the key findings from our research by meticulously outlining the experimental setup used and then starting a comprehensive analysis of the data collected. The final section emphasizes the results obtained from applying the FKF.

## 2. METHODS

### 2.1. Improve NLOS states

NLOS states are used when the conversation between the device and the tag is not direct, so the most fundamental change to improve these situations is to change the environment or location of the sensors [2], [3]. Still, in real life, we can't always put the devices in the imagined places. Because we can't prevent the tag from hiding behind something within the distance of the device, it is better to improve the NLOS states. It was made by using structures that used many methods. These methods are optimization algorithms, clustering and filtering techniques, NLOS identification methods [4]–[8] and NLOS error mitigation methods.

Several studies have been conducted on improving UWB positioning based on the optimization algorithm. One of the approaches used for enhancing indoor positioning accuracy with UWB sensors is the time of flight (TOF) calculation combined with the big bang-big crunch optimization method. The results showed a significant improvement of 27.5% in positioning accuracy [9].

Several studies have shown NLOS identification methods. It has been shown that NLOS state identification can be made in NLOS scenarios using maximum likelihood localization estimation (MLLE) and a two-layer Kalman filter [10]. The Kalman filter has demonstrated in other studies that it can do this using the help of artificial intelligence (AI). For example, Among the five different structures of convolutional neural network (CNN), including linear support vector machine (LinSVM), radial basis function support vector machine (RbfSVM), fully convolutional network (FCN), residual network (ResNet), and encoder (Enc), FCN, ResNet, and Enc have been shown to have the best accuracy [11] or expectation maximization for gaussian mixture models to classify LOS and NLOS components. The simulation was used to carry out the experiment, and the outcomes demonstrate that 86.50% accuracy can be achieved when editing both LOS and NLOS signals [12]. To distinguish between LOS and NLOS, a technique utilizing the Morlet wave transform (MWT) and CNN is suggested. Based on the results of the simulation, the MWT-CNN method provides 100% accuracy in office settings [13]. When CNN is utilized for automatically identifying and extracting features, long short-term memory (LSTM) is employed for categorization. By contrasting various configurations, the effectiveness of this approach has been examined, and the findings indicate that CNN-LSTM produces the best classification performance. The hyperbolic positioning algorithm improves location accuracy [14]. The approximate positioning algorithm using five lines gave results 4.8 cm more accurate than the algorithms using three or four lines according to static and dynamic positioning tests. Using four lines gives results 20.1 cm more accurate than the three lines algorithm. Therefore, it is recommended to use the approximate positioning algorithm using five lines [15].

Several studies have utilized clustering and filtering techniques in UWB positioning. The weighted least squares-robust Kalman filter (WLS-RKF) method was used with the Kalman filter in studies to improve NLOS conditions [16], and improvement was observed. In the study [17], final prediction error (FPE), weighted cross-entropy (WCE), and least-squares estimation (LLSE) algorithms were compared, and it was seen that LLSE was more successful than the others. Also compared LLSE, WCE, maximum likelihood estimation (MLE), and ultra-wideband-extended Kalman filter (UWB-EKF) methods and found that the UWB-EKF positioning algorithm was better than the LLSE algorithm [18]. In another study [19], the Fang, Chan, and Taylor algorithms were analyzed in NLOS conditions. It was discovered through comparative simulation analysis that, in the presence of Gauss noise, the Chan method performed the best, regardless of the number of anchors. On the other hand, the Fang algorithm performed the poorest and the Taylor method came in second. Furthermore, for the Chan and Taylor algorithms, the number of anchors lost significance after it reached a certain value. suggested a way to improve UWB location accuracy in a different research by integrating Kalman filtering and k-means clustering algorithms. The obtained UWB signals were divided into several groups using the k-means clustering technique, enabling more [20].

**2.2. Federated Kalman filter**

Using data from several local systems, the FKF is a balancing and prediction method that generates general forecasts [21]. The process of fusing many approaches into one filter structure is called federation. FKF is used by distributed systems that do not have a centralized control point. Every local system performs measurements and runs its own Kalman filter neighborhood predictions are produced by these neighborhood filters using data from measurements and system dynamics. For the make easier, collaboration and information sharing amongst the local filters, the FKF employs a communication protocol. The local filters can exchange and update prediction data with one another thanks to this protocol. Therefore, by combining data from other systems, each local filter may produce overall forecasts that are more accurate. The overall procedure for federated filtering can be summarized as follows:

**2.2.1. Initialization of filters and setting initial values**

The initial state estimate and error covariance matrix are initialized to 0 or the previously calculated value. The same operations should be performed for the error covariance matrix. These values are only used when starting the calculation. These values are updated after each calculation.

**2.2.2. Update and information sharing**

First, the primary purpose of the FKF is to combine the forecasts to improve the accuracy and reliability of local forecasts. How this fusion process is performed can be expressed mathematically. Initially, system and measurement equations for models generating data from existing sensors are defined:

$$x(k + 1) = \Phi(k)x(k) + w(k) \tag{1}$$

In (1) relates the state at the next time step ( $x(k + 1)$ ) with the current state ( $\Phi(k)x(k)$ ) and system noise ( $w(k)$ ) indicating uncertainties in the model,  $\Phi(k)$  is the system matrix, defining how the state evolves.

$$z_i(k) = H_i(k)x(k) + v_i(k) \tag{2}$$

The (2) shows how the measurement of the ith sensor ( $z_i(k)$ ), the current state ( $x(k)$ ) and the measurement noise ( $v_i(k)$ ) are related. Subsequently, how local estimates (predictions from each sensor) are combined with the global estimate is determined.

$$\sum_{i=1}^N \beta_i = 1 \tag{3}$$

In (3) states that the sum of all information sharing coefficients ( $\beta_i$ ) equals 1, meaning information is entirely shared among all local filters. In this study, equal coefficients are used for each sensor. In this study used to sensor devices have similar features so we take the  $\beta=0.5$

$$P_i^{-1}(k - 1|k - 1) = \beta_i P_g^{-1}(k - 1|k - 1) \tag{4}$$

In (4) indicates that the inverse of each local filter’s error covariance matrix ( $P_i^{-1}$ ), is proportionally adjusted with the inverse of the global error covariance matrix ( $P_g^{-1}$ ), and the coefficient  $\beta_i$ . The covariance matrix represents the uncertainty of the estimated position. The smaller the P value, the higher the confidence level in the Kalman filter’s initial prediction.

$$Q_i^{-1}(k - 1) = \beta_i Q_g^{-1}(k - 1) \tag{5}$$

Similarly, (5) adjusts the inverse of each local filter’s process noise matrix ( $Q_g^{-1}$ ) proportionally with the inverse of the global process noise matrix ( $Q_g^{-1}$ ) and the coefficient  $\beta_i$ . The process noise signifies the uncertainties in the model. A lower Q value indicates a more stable system and a slower adaptation of the prediction.

$$\hat{x}_i(k - 1|k - 1) = \hat{x}_g(k - 1|k - 1) \tag{6}$$

The (6) states that the initial prediction in each local filter ( $\hat{x}_i$ ), is the same as the global prediction ( $\hat{x}_g$ ), meaning local filters are initiated with the global prediction.

### 2.2.3. Application of Kalman filter equations

This information restructures local systems, and Kalman filtering equations are applied. In other words, predictions and updates of local filters begin. Updates are conducted as follows: each sensor is assigned a unique Kalman filter, allowing all filters to operate in parallel and generate their state estimation ( $\hat{x}_i$ ) (7) and error covariance matrix ( $P_i$ ) (8).

$$\hat{x}_i(k|k-1) = \Phi(k-1)\hat{x}_i(k-1|k-1) \quad (7)$$

$$P_i(k|k-1) = \Phi(k-1)P_i(k-1|k-1)\Phi^T(k-1) + Q_i(k-1) \quad (8)$$

Where (8),  $\Phi(k-1)$  is the system matrix,  $Q_i(k-1)$  is the process noise covariance matrix. In this study,  $Q$  was chosen as a 4×4 corner matrix with a value of 0.0003. Then, the produced state estimation ( $\hat{x}_i$ ) (10) and error covariance matrix ( $P_i$ ) (11) are updated with the Kalman gain ( $K_i$ ) (9).

$$K_i(k) = P_i(k|k-1)H_i^T(k) \times [H_i(k)P_i(k|k-1)H_i^T(k) + R_i(k)]^{-1} \quad (9)$$

$$\hat{x}_i(k|k) = \hat{x}_i(k|k-1) + K_i(k)[z_i(k) - H_i(k)\hat{x}_i(k|k-1)] \quad (10)$$

$$P_i(k|k) = [P_i^{-1}(k|k-1) + H_i^T(k)R_i^{-1}(k)H_i(k)]^{-1} \quad (11)$$

Where (9), (10) and (11)  $H$  is the measurement matrix,  $R$  is the noise covariance matrix, and  $z_i(k)$  is the measurement vector.  $R$  was selected as a 2×2 corner matrix in this study, and its value was 1.178. The gain determines how much of the difference between the estimated state and the actual measurement should be added to the prediction. If the gain is low, the measurement has little impact on the prediction. Conversely, a high gain means the measurement heavily influences the prediction. A lower  $R$ -value signifies more reliable measurements.

### 2.2.4. Optimal combination of local estimates

Selecting appropriate information-sharing coefficients is critical in applying FKF. These coefficients determine how local predictions are combined with global predictions. The global prediction is obtained by combining local predictions:

$$P_g^{-1}(k|k) = \sum_{i=1}^N P_i^{-1}(k|k) \quad (12)$$

$$\hat{x}_g(k|k) = P_g(k|k) \sum_{i=1}^N P_i^{-1}(k|k) \hat{x}_i(k|k) \quad (13)$$

where  $P_g(k|k)$  is the global error covariance matrix can be seen (12),  $\hat{x}_g(k|k)$  is the global state estimation can be seen in (13) and  $N$  is the number of sensors. A federated filter was used by the two dimensional. The position of the tag, which is fixed on the coordinate plane, was tried to be estimated with model system and measurement given by (14) and (15).

$$\begin{bmatrix} p_k^x \\ v_k^x \\ p_k^y \\ v_k^y \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} p_{k-1}^x \\ v_{k-1}^x \\ p_{k-1}^y \\ v_{k-1}^y \end{bmatrix} \quad (14)$$

$$z(k) = \begin{bmatrix} p_k^x \\ p_k^y \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} p_k^x \\ v_k^x \\ p_k^y \\ v_k^y \end{bmatrix} + v_i(k) \quad (15)$$

It is important to note that while federated filtering results are globally optimal, the solutions obtained from individual local filters may be suboptimal due to the upper bounds imposed on their covariance matrices. Amplifying the noise covariance can degrade the accuracy of local estimates and fault detectability. Therefore, a fault in a subsystem that goes undetected before the fusion process can contaminate the global system and affect the fault-free local filters. To improve fault tolerance, it is recommended not to use the reset mode of the federated filter, but this may result in the global solution being

no longer optimal [22], [23]. The federated filtering technique's use of information sharing has the tree main benefits, first enhanced measurement data throughput by concurrent local filter operation and internal data compression. Secondly, Improved system fault tolerance by maintaining numerous component solutions to increase fault detection and recovery capabilities. Finally, by employing theoretically sound estimate techniques, cascaded filter operations are more accurate and stable [24].

**2.3. Experimental setup**

The necessary data for this study was gathered at Kadir Has University, within an environment measuring 7.35×5.41 m. The floor of the territory was marked at intervals of 0.50 m. Using these marked points, a route resembling a butterfly shape was defined by connecting ten fixed points, from which the data was collected, as shown in Figure 1.

The marked floor facilitated the determination of the actual positions of these fixed points. This allowed for the observation of discrepancies between the measured values and the actual values. Four anchors (gateway UWB sensors) and two tags (UWB sensors) were employed during the data collection. The anchors were suspended from the ceiling system, maintaining a constant height of 2.85 m in all corners of the testbed (designated as A0, A1, A2, and A3 in Figure 2). The Decawave MDEK1001 UWB development kit [25] was used to execute this experiment, incorporating the test tag. The data was collected in NLOS and LOS scenarios.



Figure 1. Scenario for the 7.35×5.41 m testbed area

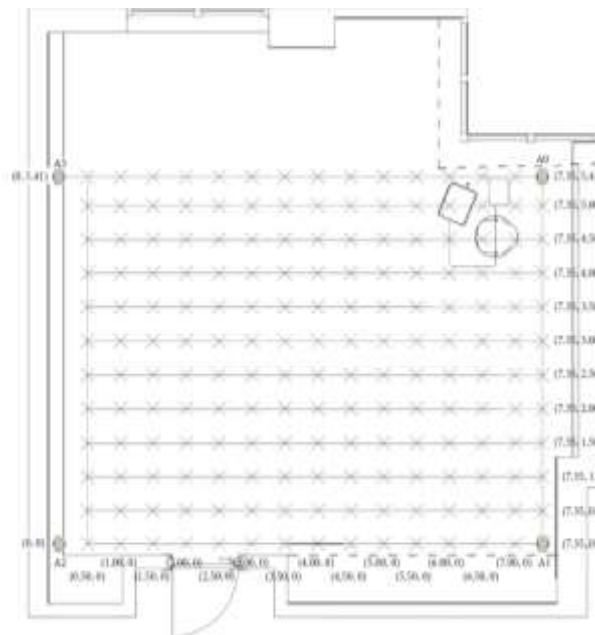


Figure 2. Testbed area of 7.35×5.41 m

## 2.4. Creating dataset

The data was collected under two distinct conditions during the collection process: LOS and NLOS. Each tag was initially operated individually, and data was collected at each specific point. Subsequently, to assess whether the concurrent operation of the sensors influenced location accuracy, both tags were operated simultaneously at the exact location, and data was gathered. In the NLOS data collection scenario, unlike the LOS scenario, the data collecting scenario involved placing the tags in the same pocket of a garment to guarantee that they were exposed to NLOS circumstances while a human body was present. In the next section, the gathered data were examined to determine the error conditions for the two cases in which the tags were used alone and in pairs at each particular location.

## 3. RESULTS AND DISCUSSION

A technique for evaluating the discrepancy between measured and real values is represented by the formula utilized in this study. The idea of Euclidean distance serves as the foundation for this formula. It computes the coordinate differences in a two-dimensional space between a real point and a measured point. From a mathematical perspective, the formula can be seen in (16).

$$Error = \sqrt{((X_{actual} - X_{measured})^2 + ((Y_{actual} - Y_{measured})^2)} \quad (16)$$

Where the coordinates of the calculated values are represented by X\_measured and Y\_measured, while the coordinates of the actual values are represented by X\_actual and Y\_actual. After squaring these differences and summing them, the square root of the total value is taken. This result is used to determine how close or far apart two points are from each other.

This error analysis method is typically used when comparing predictions or measurements to actual values. The obtained result indicates the magnitude of the difference between actual and measured values. Lower results indicate that the measured values are closer to the actual values, while higher results indicate larger errors. Subsequently, the average of these error values is calculated for each point. The values after applying the FKF to the data collected by running them individually and in pairs while in motion in LOS and NLOS situations give the results as shown in Tables 1 to 4. The unit of errors is the meter.

Table 1. In cases where the tags are individually and LOS conditions are present, error scenarios

ID	Point 1	Point 2	Point 3	Point 4	Point 5	Point 6	Point 7	Point 8	Point 9	Point 10	Total error
<b>Tag1</b>	0.1525	0.1495	0.2059	0.1021	0.2947	0.3835	0.3468	0.3693	0.1906	0.1200	<b>0.2315</b>
<b>Tag2</b>	0.1520	0.1213	0.2396	0.1224	0.3115	0.3182	0.3093	0.2667	0.1237	0.1669	<b>0.2132</b>

Table 2. In cases where the tags are individually and NLOS conditions are present, error scenarios

ID	Point 1	Point 2	Point 3	Point 4	Point 5	Point 6	Point 7	Point 8	Point 9	Point 10	Total error
<b>Tag1</b>	2.7576	4.9666	5.1663	4.8009	5.8701	4.6540	3.1989	4.5464	5.2367	2.4930	<b>4.3690</b>
<b>Tag2</b>	2.0264	4.3047	5.5194	3.1821	4.5827	1.6564	3.8367	4.9599	3.9500	3.0357	<b>3.7054</b>

Table 3. In cases where the tags are pairs and LOS conditions are present, error scenarios are used

ID	Point 1	Point 2	Point 3	Point 4	Point 5	Point 6	Point 7	Point 8	Point 9	Point 10	Total error
<b>Tag1</b>	0.2591	0.2950	0.2701	0.2984	0.3050	0.2716	0.2879	0.2958	0.3453	0.3234	<b>0.2952</b>
<b>Tag2</b>	0.1729	0.1719	0.2947	0.1729	0.3255	0.4627	0.3296	0.4337	0.1474	0.1793	<b>0.2691</b>

Table 4. In cases where the tags are pairs and NLOS conditions are present, error scenarios are used

ID	Point 1	Point 2	Point 3	Point 4	Point 5	Point 6	Point 7	Point 8	Point 9	Point 10	Total error
<b>Tag1</b>	4.7535	7.7296	3.0798	4.5937	5.3731	8.1867	4.0007	4.4737	6.4654	2.0129	<b>5.0669</b>
<b>Tag2</b>	2.8704	8.0547	3.2606	3.9518	5.6892	7.2822	2.9155	2.5592	2.8404	3.0468	<b>4.2471</b>

In LOS environment studies, it was observed that there was an average improvement of approximately 96.64% following the application of the FKF. Tables 5 and 6 demonstrate the impact of FKF on tags in LOS conditions. In NLOS conditions, an average improvement of approximately 96% was observed after applying the FKF in the studies. This means that the error margin, about 5 m, was reduced to 0.12 m. Tables 7 and 8 demonstrate the impact of FKF on tags in NLOS conditions.

Table 5. The tags are individually, and LOS conditions are present, error scenarios after the application of FKF

ID	Point 1	Point 2	Point 3	Point 4	Point 5	Point 6	Point 7	Point 8	Point 9	Point 10	Total Error
<b>Tag1</b>	0.0050	0.0050	0.0094	0.0033	0.0095	0.0124	0.0110	0.0121	0.0056	0.0038	<b>0.0077</b>
<b>Tag2</b>	0.0051	0.0050	0.0075	0.0049	0.0105	0.0101	0.0103	0.0085	0.0042	0.0060	<b>0.0072</b>

Table 6. The tags are pairs, and LOS conditions are present, error scenarios after the application of FKF

ID	Point 1	Point 2	Point 3	Point 4	Point 5	Point 6	Point 7	Point 8	Point 9	Point 10	Total Error
<b>Tag1</b>	0.0083	0.0062	0.0071	0.0044	0.0092	0.0135	0.0121	0.0142	0.0082	0.0088	<b>0.0092</b>
<b>Tag2</b>	0.0059	0.0053	0.0076	0.0039	0.0116	0.0135	0.0103	0.0141	0.0037	0.0067	<b>0.0083</b>

Table 7. The tags are individual, NLOS conditions are present, and error scenarios after the application of FKF

ID	Point 1	Point 2	Point 3	Point 4	Point 5	Point 6	Point 7	Point 8	Point 9	Point 10	Total Error
<b>Tag1</b>	0.0936	0.1618	0.1784	0.1557	0.1941	0.1489	0.1069	0.1364	0.1737	0.0807	<b>0.1430</b>
<b>Tag2</b>	0.0644	0.1393	0.1936	0.1011	0.1471	0.0495	0.1242	0.1574	0.1409	0.0955	<b>0.1213</b>

Table 8. The tags are pairs, and NLOS conditions are present, error scenarios after the application of FKF

ID	Point 1	Point 2	Point 3	Point 4	Point 5	Point 6	Point 7	Point 8	Point 9	Point 10	Total Error
<b>Tag1</b>	0.1570	0.2456	0.0944	0.1583	0.1769	0.2634	0.1269	0.1518	0.2170	0.0652	<b>0.1657</b>
<b>Tag2</b>	0.0847	0.2708	0.1006	0.1277	0.1853	0.2389	0.0720	0.0758	0.0943	0.1008	<b>0.1351</b>

Furthermore, it was observed that in scenarios where multiple mobile devices were present in environments accommodating both conditions, the error rate was higher. The results of the experiment, evident in Tables 3, 4, 6, and 8 showed that the devices performed worst when operated in pairs. These tables revealed that paired devices had a higher average error rate compared to those operated individually.

#### 4. CONCLUSION

In order to increase the accuracy of UWB-based positioning devices in NLOS situations, this paper focuses on using FKF. More precise position estimate is achieved by merging data from many local systems using the FKF. The location accuracy is enhanced beyond a certain range when the FKF is utilized, according to the results reported in the article. In studies conducted within LOS environments, implementing the FKF resulted in an average accuracy enhancement of about 96.64%. The error margin, up to 0.30 m, decreased to 0.0072 m thanks to FKF. A comparable improvement of almost 96% was seen in NLOS scenarios, demonstrating the filter's adaptability to many environmental circumstances. The margin of error is now only 0.12 m because to FKF. The FKF outperforms the classical Kalman filter primarily because it can work with many sensors at once and give each sensor a distinct weighting coefficient. This feature uses a strong feedback and update mechanism to successfully eliminate incorrect states. Such features enable the FKF to yield more accurate results, especially in environments characterized by sensor integrations or high error probabilities. However, the FKF method can also be a localization method when tag devices are in the exact location. Overall, the findings presented in this article demonstrate the superiority of FKF over conventional Kalman filters in complex scenarios, underlining the promising role of federated Kalman filtering in improving the accuracy of UWB-based positioning devices in various environmental conditions. The following work area will implement the Federated Kalman Filter in moving objects and examine different source NLOS situations.





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