

# LSTM-based System for Multiple Obstacle Detection using Ultra-wide Band Radar

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**Abstract:** Autonomous vehicles present a promising opportunity in the future of transportation systems by providing road safety. As significant progress has been made in the automatic environment perception, the detection of road obstacles remains a major challenge. Thus, to achieve reliable obstacle detection, several sensors have been employed. For short ranges, the Ultra-Wide Band (UWB) radar is utilized in order to detect objects in the near field. However, the main challenge appears in distinguishing the real target's signature from noise in the received UWB signals. In this paper, we propose a novel framework that exploits Recurrent Neural Networks (RNNs) with UWB signals for multiple road obstacle detection. Features are extracted from the time-frequency domain using the discrete wavelet transform and are forwarded to the Long short-term memory (LSTM) network. We evaluate our approach on the OLIMP dataset which includes various driving situations with complex environment and targets from several classes. The obtained results show that the LSTM-based system outperforms the other implemented related techniques in terms of obstacle detection.

## 1 INTRODUCTION

Seemingly during few years, autonomous vehicles have turned a major interesting topic for researchers. This is due to the exploitation of artificial intelligence in the automotive field, which opened the way to the deployment of self-driving cars. In fact, self-driving cars have the potential to radically transform the road's environment by saving road users' lives, reducing pollution and fuel savings (Skrickij et al., 2020) (Khalifa et al., 2020).

Real-time obstacle detection is one of the main challenges presented in developing perception systems for Intelligent Transportation Systems (ITS) (Tarchoun et al., 2020b) (Tarchoun et al., 2020a). To achieve this, an ITS deploys numerous sensors. The widely employed sensors are cameras, lidar and radar sensors (Kocić et al., 2018). These sensors can be

used in different circumstances, as each sensor has typical advantages and disadvantages in this field of research (Jegham et al., 2018). In this work, we focus our attention on radar sensors.

The radar is a radio frequency-based sensor that transmits electromagnetic waves and determines the vehicle surrounding characteristics based on the reflected echo. Recently, the radar sensor has played a key role in military applications (Lee et al., 2020), people counting (Choi et al., 2017) and positioning (Nguyen and Pyun, 2015), and it is specifically employed in the automotive field (Hakobyan and Yang, 2019). In fact, the radar is able to detect obstacles in the vehicle's surrounding by estimating their range, velocity and angle. It is robust to bad weather conditions like the fog and rain, and it is not affected by poor light circumstances. Furthermore, it is employed in short and long distances depending on the developed advanced driver assistance systems. In fact, narrow-band radars are specially utilized to detect obstacles in long ranges. For short range applications, the Ultra-Wide Band (UWB) technology is the most exploited in this area of research as it provides rich

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information. The UWB radar emits narrow pulses with low energy in the order of picoseconds to few nanoseconds (Saito et al., 2003). This type of radar has been in the spotlight owing to its high resolution, good penetration rate, and anti-interference ability acquired from other devices (Zetik et al., 2007).

The preeminent property of such a radar consists in the deformation of the emitted pulse. This distortion depends on the obstacle's characteristics, thereby it is labeled as the object signature. This signature is impacted by the object shape, material and size. For example, the signature of a metallic object has higher amplitude than a pedestrian one. Accordingly, the employment of such a technology remains promising to detect objects in near ranges. The data acquired from the UWB radar can be represented under two forms: a 1 dimensional (1D) signal, which is the reflected echo, and 2 dimensional (2D) data that can be a 2D feature map or a converted image.

Despite the fact that the UWB radar provides rich information, one of the fundamental challenges that could occur is distinguishing the real target's signature from noise. For this purpose, various studies have been conducted by proposing UWB-based detectors. These detectors can be characterized into two categories: hand crafted-based systems and deep learning-based systems.

The most popular hand crafted-based detection algorithms are: the correlation technique (Sakkila et al., 2006), the Constant False Alarm Rate (CFAR) (Rohling, 1983) based techniques and the Higher Order Statistics (HOS) (Mendel, 1991). The aforementioned algorithms have been exploited ever since the development of the conventional radar. CFAR-based approaches analyze the characteristics of the signal's noise in order to define a threshold. The target is detected if its magnitude is above the defined threshold. A HOS-based technique is a correlation-based method that uses higher-order moment spectra.

Currently, with the significant advancements conducted by deep learning techniques, there exist various studies that have investigated it with UWB signal measurements, particularly in indoor environments (Briso et al., 2019) (Tong et al., 2020) (Kumar et al., 2019). Even though the interest of processing UWB data via deep learning techniques is growing, there is no work that has deeply treated UWB signals for outdoor environment perception to the best of our knowledge. In this paper, we propose the first framework that exploits UWB signals with a Long Short-Term Memory (LSTM) network in an outdoor environment involving complex urban driving situations for multi-target detection. As the received UWB signal is time-series data, the exploitation of a RNN is suitable to ex-

hibit the temporal dependencies. Therefore, the main intention of the developed network is to discriminate the real target from noise within a received UWB signal.

In this work, the main contributions are the following:

- An overview of the existing deep learning-based methods using UWB signals is presented.
- A proposal of the first framework that exploits LSTM with UWB signals for multi obstacle detection in an outdoor complex environment.
- A comparison between our suggested approach and the state-of-the-art techniques based on expanded experiments using an extensive environment perception dataset (Mimouna et al., 2020) is detailed. The obtained results show that our method outperforms the conventional techniques.

The remainder of this paper is arranged as follows. In section 2, a review of related work using UWB signals is presented. The proposed approach is detailed in section 3. In section 4, we expose the experimental setup and the obtained results. Finally, we conclude the paper in section 5.

## 2 RELATED WORK

In subsection 2.1, we present the reviewed work that relies on using the UWB radar with hand-crafted detectors. For subsection 2.2, we review the deep UWB-based systems.

### 2.1 Hand-crafted UWB-based Systems

Most of the studies on UWB-based obstacle detection systems have taken advantage of the well-known correlation technique, CFAR and HOS techniques. These techniques are known as hand-crafted based detectors. In (Sakkila et al., 2008), the correlation was used to detect either a car, a metal plate, a motorway barrier or a pedestrian. The HOS technique was commonly employed to suppress the Gaussian noise (Mendel, 1991). Several algorithms have been extended from the CFAR including the Cell Averaging CFAR (CA-CFAR) (Conte et al., 1988), the order static CFAR (Blake, 1988), the Smallest Of CFAR (Cai et al., 2010), etc. A new thresholding method based on the CFAR technique for UWB-based detection application was put forward in (Quan et al., 2020). The approach took into consideration false alarm and miss-detection criteria. A new parameter, entitled constant miss-detection rate (CMDR), is defined. The final threshold was calculated by adding

the CFAR and CMDR rates. The experiments showed good performances, although they were just carried out in indoor environment using self-recorded dataset. In the work presented in (Kim, 2020), metal lanes would be detected if the energy value of the received UWB signal surpassed a defined threshold. In (Sadli et al., 2018), a UWB radar detector for ITS applications was proposed by combining the CA-CFAR and HOS techniques. Nevertheless, the experiments were performed under controlled scenarios.

In fact, most of the aforementioned related work has been a threshold-based methods. Otherwise, these techniques depend essentially on the amplitude of the object's signature. Moreover, it should be pointed that the considered environment and scenarios are controlled using restrained datasets.

## 2.2 Deep Learning UWB-based Systems

To the best of our knowledge, UWB-based systems that rely on deep learning techniques have been employed only for indoor applications such as: activity recognition (Sadreazami et al., 2018), indoor people localization (Poulouse and Han, 2020) and recognition of movements during sleep (Piriyajitakonkij et al., 2020).

Deep learning methods have been used with 2D UWB data, so, this dilemma is considered as an image processing-based challenge. In (Chen et al., 2019), an SFCW-UWB radar was used for fall detection, which generated a time-frequency spectrum as UWB data. Hence, the employed deep learning architecture was the fine-tuned Alexnet model. The authors in (Ko and Lee, 2016) converted the time-series UWB data to a time-frequency representation by Stockwell transform. Afterwards, the reshaped images serve as inputs of the Convolutional neural network(CNN). The exploited CNN model was LeNet. In (Ahmed and Cho, 2020), UWB data were stored as a 2D matrix including the slow-time and the fast-time properties. Subsequently, it was converted to a grayscale image, and later to an RGB one. GoogLeNet was adopted as a deep learning architecture for hand gesture recognition.

In fact, 2D radar imaging based systems are no longer considered a signal processing dilemma, but rather an image processing challenge.

Otherwise, 1D UWB signals are likewise employed with deep learning for indoor applications.

To enhance transportation safety, a UWB radar is installed in the rear view mirror to estimate the number and location of the in-vehicle people. A multi-layer perception is employed where the time-sampled radar signal data are the input of the network. To de-

fine the suitable parameters, the number of hidden layers is adjusted. Compared to machine learning techniques, the suggested network achieves better results (Lim et al., 2020). For activity recognition, a CNN-LSTM network using three UWB radars is implemented in (Maitre et al., 2021). The features are extracted using a CNN architecture that includes: two 1D convolution layers with 64(1x3) filters, a Relu activation function, and a 1D max pooling layer. Subsequently, the output is flattened in to a 1D vector to feed the LSTM network that contains 2 LSTM layers. Promising results are obtained. Jiang et al. (Jiang et al., 2020) trained a CNN-LSTM to classify Line-Of-Sight and None-Line-Of-Sight signals in the context of indoor positioning applications. The UWB channel impulse response was used as input of the CNN that deployed two conventional layers. Afterwards, the CNN outputs were linked to the LSTM network. A bi-direction LSTM and a stacked LSTM were used. The achieved accuracy was equal to 81%, but the training dataset was limited.

The aforementioned applications have considered only indoor environments, using either 2D radar imaging or 1D UWB data. Nevertheless, the ITS environment includes complex driving situations with various types of targets. Moreover, in our case, the choice of adopting a 1D radar signal rather than using a 2D radar data representation is justified by the fact that we deal with an ITS application where response time is a crucial criterion.

## 3 PROPOSED METHOD

The received UWB radar signal is time-series data, so, the adoption of the LSTM is recommended. Thus, in this section, we firstly present the background of the LSTM network, followed by a description of the proposed approach.

### 3.1 LSTM Background

The LSTM network is a special architecture of the artificial RNN developed in 1997 by Hochreiter and Schmidhuber (Hochreiter and Schmidhuber, 1997). It was introduced to avoid the issues that would occur when modeling long-term dependencies with RNN such as the vanishing or exploding gradient problem. Therefore, the LSTM network is able to learn short-time as well as long-term dependencies. It is especially known by its effectiveness to treat time-series data (Ameur et al., 2020). In other words, the LSTM network is able to model the temporal changes in a series of data owing to its memory units and recur-

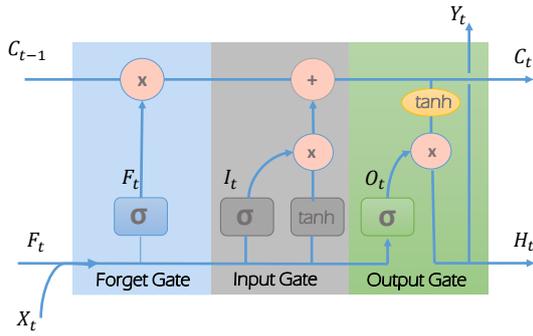


Figure 1: Architecture of LSTM unit.

rent architecture. The LSTM units are connected sequentially. Each LSTM cell includes its own memory with three gates: the input, the output and the forget gates. These gates are responsible for protecting and controlling the flow of information through the cell. Otherwise, they decide which information has to be forgotten or reminded. The LSTM cell is expressed by Equation 1 and detailed in Figure 1:

$$\begin{cases} I_t = \sigma(W_I[H_{t-1}, X_t] + b_I) \\ F_t = \sigma(W_F[H_{t-1}, X_t] + b_F) \\ O_t = \sigma(W_O[H_{t-1}, X_t] + b_O) \\ C_t = F_t * C_{t-1} + I_t * \tanh(W_C[H_{t-1}, X_t] + b_C) \\ H_t = O_t * \tanh(C_t) \\ Y_t = \text{softmax}(W_Y H_t + b_Y) \end{cases} \quad (1)$$

where:

- $X = \{X(1), X(2), \dots, X(N)\}$  is an input sequence, where  $N$  is the length of the time series sequence.
- $I_t$ ,  $F_t$ ,  $O_t$  and  $C_t$  are respectively the input, the forget gate, the output gates and the memory cell state.
- $H_t$  is the cell output and  $Y_t$  is the final output.
- $\tanh$  and  $\sigma$  are respectively the hyperbolic tangent and the logistic sigmoid activation functions.
- $W$  and  $b$  are respectively the input weights, associating the LSTM cell to the inputs, and the bias vectors.

### 3.2 Proposed UWB-based System for Obstacle Detection

Despite the fact that UWB reflected signal incorporates rich information, the discrimination between the object's signature from noise is a fundamental challenge. The received UWB signal  $r(t)$  can be modeled following Equation 2:

$$r(t) = s(t) + n(t) \quad (2)$$

where  $s(t)$  is the received echo and  $n(t)$  is the noise of the transmission channel of the UWB radar.

In fact, the process of emitting and receiving an impulse by the UWB radar is labeled as a radar scan, and the received echo of the  $j^{\text{th}}$  radar scan  $s_j(t)$  is presented by Equation 3:

$$s_j(t) = \sum_{k=1}^{N_j} a_{jk} x(t - t_{jk}) \quad (3)$$

where:  $x(t)$  is the emitted pulse which is acquired as  $N_j$  reflected signals,  $a_{jk}$  is the amplitude. And,  $t$  and  $t_{jk}$  are respectively the reflection duration of the pulse after the transmission process and the delay of the  $k^{\text{th}}$  received echo in the  $j^{\text{th}}$  radar scan.

Thereby, based on the UWB property that indicates that each obstacle has its own signature, noise also should be different.

On the other hand, the target's wave reflection amplitude is generally changing over time due to physical characteristics (material, shape, size, etc.), and it gets attenuated when moving away from the radar sensor. Otherwise, the received echo is a function of time, and is also a function of the obstacle distance from the sensor. This time-distance relation is expressed by Equation 4:

$$R = \frac{\tau c}{2} \quad (4)$$

where  $\tau$  and  $c$  are respectively the delay between the transmission and reception of the UWB pulse, and the speed of light.

Hence, based on the temporal changes presented in the UWB signal and the fact that the noise partitions should be different from a real object's signature, we adopt the idea of employing the LSTM network. This choice is made on account of the fact that this type of RNNs is able to recognize and synthesize the dynamics variations within the received UWB echo. Thereby, in this work we put forward the first framework that exploits the LSTM network with UWB signals for distinguishing obstacles from noise in a vehicle environment perception context.

The proposed framework is explained in Algorithm 14 and represented in Figure 2. Primarily, the received signal is split into time series sequences  $[X_t]$ . These sequences present the useful regions which contain the real targets (illustrated by the orange windows in Figure 2) and noise partitions (depicted by green rectangles in Figure 2). For data variety, the noise parts are randomly selected from the UWB signal. In fact, the window's size ( $W_{sig}$ ) is empirically set according to the objects' signature length. Afterwards, features from the time-frequency domain are extracted from the defined regions. Thus, the Discrete Davelet Transform (DWT) is utilized. We extract four features from the approximation coefficients ( $Ca$ ) and

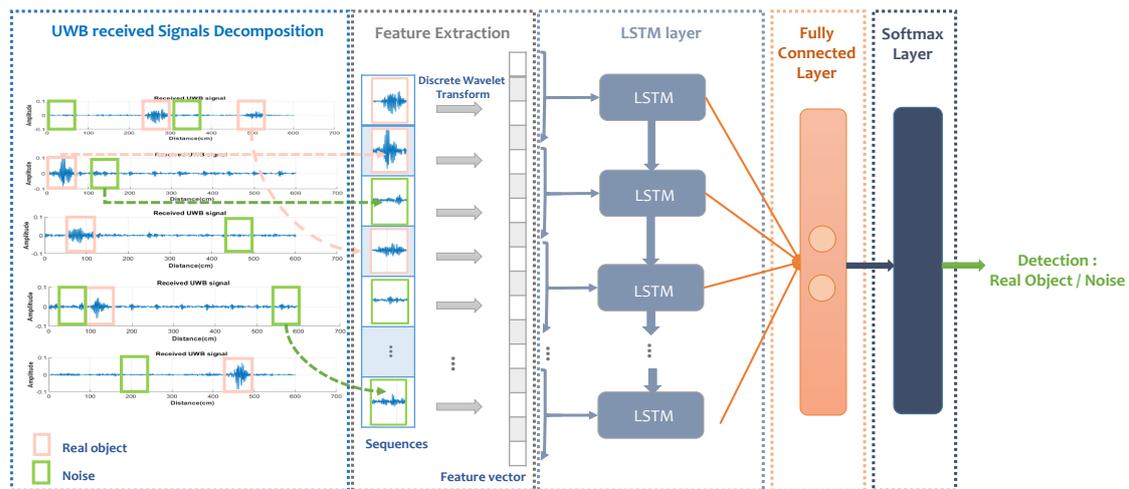


Figure 2: Proposed LSTM-based framework using UWB signals.

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Algorithm 1: LSTM-based algorithm for obstacle detection using UWB signals.

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**Data:** Received signal  $r = [r_t]$ , Signature window length:  $W_{sig}$ ;  $LSTM_{options}$ ; Position:  $pos$

**Output:** Class

```

1 // Split time series into sequences
2 for  $t \leftarrow pos$  to  $length(W_{sig})$  do
3    $X_t = r(pos, t + pos)$ ;
4 end for
5 // Extract features using the DWT
6  $Fvector = []$ 
7  $[Ca, Cd] = DWT(X_t)$ 
8  $F1 = mean(Ca); F2 = std(Ca); F3 = min(Cd); F4 = rms(Cd)$ 
9  $Fvector = append(Fvector, F1, F2, F3, F4)$ 
10 // Feed the LSTM-based network
11  $Output_{LSTM} = LSTM(Fvector, LSTM_{options})$ 
12  $Output_{FCL} = Fullyconnectedlayer(Output_{LSTM})$ 
13  $Class = Softmax(Output_{FCL})$ 
14 return (Class)

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the detail ones ( $Cd$ ) for each sequence. Subsequently, the fattened 1D descriptor vector feeds the LSTM network. Finally, the output of the LSTM is linked to the fully connected layer of size 2 followed by a Softmax layer and a classification layer.

To conclude, the suggested detector analyzes the temporal changes within the UWB signal via learning the extracted time-frequency features that highly present the signal characteristics in order to differentiate a real target from noise.

## 4 EXPERIMENTS

To highlight the efficiency of the proposed architecture, we compare it to the implemented state-of-the-art techniques: CA-CFAR, HOS and the work in (Sadli et al., 2018). Furthermore, we conduct our experiments on a variety of urban driving scenarios. In this section, we provide the experimental setup and the obtained results. The experimental results are evaluated using the Precision (P), Recall (R) and F1-score metrics.

### 4.1 Experimental Setup

The heterOgeneous Multimodal Dataset for Advanced EnvIronMent Perception (OLIMP)<sup>1</sup> is exploited in this work (Mimouna et al., 2020). It contains several urban driving situations including four main categories: pedestrian, cyclist, vehicle and tram. The dataset includes over 47 thousands of UWB signals collected under various conditions: different weather conditions (as fog, snow), near and far targets, etc. The developed radar by the UMAIN Inc company is the sensor that has been used to record the OLIMP database (Anu, 2020). It is entitled HST-D3. The radar distance range is six meters and its frequency range is [3GHZ, 4GHZ] with a bandwidth of 0.45-1GHz. The HST-D3 radar is composed of a module radar called HST-S1 Pi and a Raspberry Pi 3. In addition, The directional antennas are utilized as they guarantee a better target echo-to-clutter and noise ratio. The UWB radar signal comprises 660 samples per frame. The radar is illustrated in Figure 3.

<sup>1</sup><https://sites.google.com/view/ihsen-alouani/datasets>

Table 1: Execution time results.

	HOS	CA-CFAR	(Sadli et al., 2018)	Proposed method
Execution time (s)	1.34	1.41	1.52	2.01

For our experiments, we use 2/3 of the data for the training step and 1/3 for the test process. It shall be mentioned that for training process, we exploit the unidirectional network with 100 LSTM hidden units. The number of epochs and mini batch size during experiments are set to 100 and 64 instances respectively. Moreover, we utilize the Adam optimizer (Bock et al., 2018). The initial learning rate is set to 0.001. The optimal set of parameters is selected based on preliminary tests. For the DWT, the Daubechies wavelet (db2) is employed to extract the features from the time series sequences.

As regards to the comparative study, for the HOS we take advantage of the 4<sup>th</sup> order cumulant that relies on the Tuganit4 algorithm. Concerning the CFAR technique, the CA-CFAR detector is considered with an automatic threshold.

All the experiments are performed using Matlab 2020a on a PC with an Intel (R) core (TM) i7-8565U, CPU @ 1.8 GHz, 16 GB of RAM.

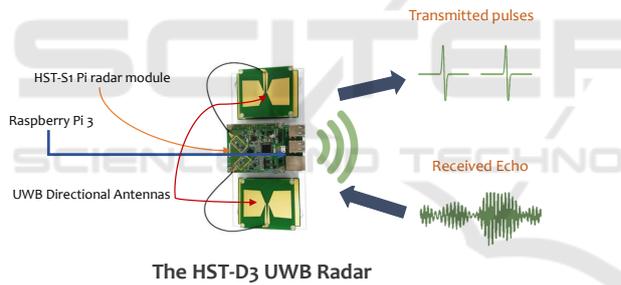


Figure 3: Used HST-D3 UWB radar hardware specifications.

## 4.2 Results and Discussion

The experimental results concerning the comparative study is illustrated in Figure 4. In fact, it can be seen from the figure that the obtained results show that our deep learning-based method achieves the highest performance. Our proposed method outperforms significantly the considered traditional detectors, particularly in terms of recall and precision.

The performance of the CA-CFAR, the HOS and their combination in the work of (Sadli et al., 2018) depend essentially on the definition of the threshold parameter. A higher threshold generates more false negatives, but, the opposite case produces additional false positives. Furthermore, the object detection rate using the aforementioned techniques rely

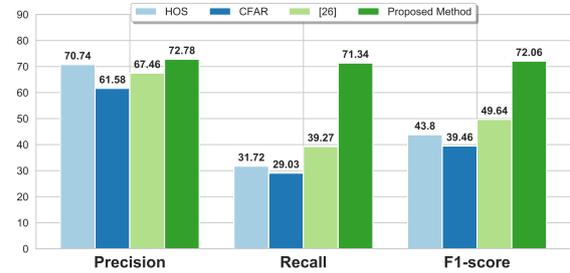


Figure 4: Experimental results using HOS, CFAR, work in (Sadli et al., 2018) and our method.

on the object's amplitude. In low magnitude cases, which means that the object is moving away from the radar, the target cannot be detected and it is considered as noise.

Compared with these techniques, the proposed system remains robust even with low amplitude cases as it is not based basically just on the object's amplitude. In fact, the LSTM-based method can distinguish noise from real targets thanks to the relevant features that are extracted from the time-frequency domain, and by learning the temporal relationship between the data sequences. The DWT reveals the structure of the signal, thus allowing the localization of its peculiar characteristics in time and frequency domains. For this reason, the time-frequency features lead to a high performance as they can represent well the signal's characteristics.

It shall be mentioned that, some missclassifications are still present due the challenges related to the interclass similarity of the obstacle's signature and the noise signal when the object's signature has a low amplitude. Accordingly, further research can be expanded to extract deep features to tackle this dilemma.

In terms of complexity, Table 1 depicts a comparison of the execution time of our method with the state-of-the-art techniques. As it can be seen from the results, our architecture has the highest execution time, though, advanced hardware resources are to be deployed to acquire faster detection time.

## 5 CONCLUSION

In this paper, we put forward a novel framework for obstacle detection using UWB signals with deep learning techniques. The developed detector focuses principally on distinguishing the real target from

noise within the received UWB signal. For this purpose, features are extracted using the DWT. These descriptors are used as inputs of the LSTM network which is exploited as a classifier. According to the extensive experiments carried out on a large dataset. Promising results are found, which outperform the performances of the related techniques. For future work, the employment of CNN to extract features from the UWB signals can be investigated.

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