The Application of Lateral Inhibition Model in Image’s Contour Enhancement and Design of Its Electro-Model

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Abstract—For overcoming the problems such as distortion and shift of object’s edge, easily losing the object detail information of methods in image edge detection, and satisfying higher demand for object detection in the modern war, a new image edge detection method was designed. LOG edge detection as a typical image processing method was introduced and the disadvantage of this model was analyzed firstly. Based on lateral inhibition theory, an acyclic lateral inhibition network model (ALINM) based on biology vision information processing mechanism was designed. The feasibility of object detection by lateral inhibition model was analyzed, in order to express the advantage such as rapid calculation easily real time operation of ALINM, the calculation magnitude of circulation difference lateral inhibition model was analyzed. Besides the correctness of ALINM was confirmed with two input cells, its transfer function was deduced. An algorithm of image edge detection based on this model was established finally, lateral inhibition effect also was confirmed by one-dimension and two-dimension circuit model based ALINM. Simulative experiment with different parameters and physics experiment prove that acyclic lateral inhibition network model can be realized easily, it can preserve the farthest detail information of object and has faster calculation speed than LOG operator. ALINM and lateral inhibition theory provide a useful method based on biology vision for object detection under difficult imaging conditions.

Index Terms—image processing, LOG operator, acyclic lateral inhibition network model, calculation magnitude, algorithm, electro-model, experiment

I. INTRODUCTION

Image’s edge has strong stability as one of the main character, it is significant to detect this edge information in image processing. There are many methods that can use to detect the object’s edge in image, and many of these kinds of methods have been used in object detection [1]. But there are different demands for edge detection methods in different application. In national defend application and aerospace application, there are higher demands like faster processing speed, correct orientation, better effect and so on for object detection.

Because some biology in nature has unique vision information processing mechanism, it has super ability in detection, orientation, recognition, track and capture, which hominine sense and existing instruments can’t attain this ability. In vision information processing, frog’s eyes, pigeon’s eyes and other biology’s compound eyes have its own ingenious configuration and unique enginery.

As one of the typical oceanic biology, the lateral inhibition network information processing mechanism of limulus’s compound eyes provide well reference for detecting image’s edge character [2]. This essay advances a method that using inhibition competition networks to detect the image’s edge. The edge detected by this method don’t change its position in primary image, when gray changes with beam, this method can also detect edge character effectively, with better resistibility to gray change as well as easy process in real time.

II. LOG EDGE DETECTION OPERATOR

LOG algorithm was advanced by Marr and Hildreth with integrating Gauss filt and Laplacian edge detection. LOG algorithm rooted from edge detection method advanced by Marr’s vision theory, initial image was taken smoothness processing to inhibit noise furthest, and then edge was detected from smoothness processed image.

Marr chose two-dimension Gauss function $g(x, y)$, as in (1).

$$g(x, y) = \frac{1}{2\pi\sigma^2} \cdot \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right). \tag{1}$$

Smoothness image $I(x, y)$ was computed by convolution, as in (2).

$$I(x, y) = G(x, y) * f(x, y). \tag{2}$$

The 2-factorial direction differential coefficient image $h(x, y)$ of smoothness image $I(x, y)$ is computed by Laplacian $\nabla^2$, as in (3) and (4).
\[ h(x,y) = \nabla^2 [g(x,y) \ast f(x,y)]. \quad (3) \]

\[ h(x,y) = [\nabla^2 g(x,y)] \ast f(x,y). \quad (4) \]

The zero locus of \( h(x,y) \) is image \( f(x,y) \)'s edge. \( \nabla^2 g(x,y) \) is LOG algorithm, as in (5).

\[ \nabla^2 g(x,y) = \frac{1}{\pi \sigma^2} \left[ 1 - \frac{x^2 + y^2}{2\sigma^2} \right] \exp\left( \frac{x^2 + y^2}{2\sigma^2} \right). \quad (5) \]

There are some disadvantages of LOG edge detector, if the edge's width less than operator's width, as the pitch fusion pass zero will lose details. LOG edge detector has the edge's width less than operator's width, as the pitch.

III. LATERNAL INHIBITION THEORY

Lateral inhibition can intensify contrast, and extrude object’s contour, so object is cleared by this processing. There are different models based on its study object, which explain lateral inhibition phenomena. Although this model are different with each other, but there is an common aspect around this models, it is said that this phenomena is an result of mutual effect between excitability function of each unit caused by outside stimulation and inhibition caused by surrounding units.

Acyclic lateral inhibition network model (it is called ALINM in this essay) is established in this section, and then the essence of lateral inhibition is proved, finally transfer function of this model is described.

A. Biologic Foundation of Lateral Inhibition

The biologic prototype of lateral inhibition theory is compound eye vision information processing system of precious oceanic biology limulus.[3] Limulus has four eyes, it is shown in Fig.1, the size of two small eyes is 0.5mm in foreside of cuirass as well as twin big plural eyes. The function of single eye is as sensor that receiving ultraviolet radiation, and the plural eyes have more than 1000 small eyes. If each eye is considered as a sensor, each sensitive cell of compound eye can focalize the light by its own lens. If there are neural twigs transit from this sensitive cells, beam translate into pulse electric current, then pulse electric current transfer into brain by neuraxon to recognize object.

The electrophysiological research of lateral inhibition network was first introduced by Hartlein and his colleagues of Rockefeller University. Because the volume of limulus’ compound eye is huge and nerve thread is wide, it brings much convenience for research, Hartlein discovered the vision lateral inhibition phenomenon of limulus and established lateral inhibition math model by limulus’ compound eye as their research object. During the research process, scientists took one port of exact micro electrode to the vision neural thread of a small eye, with the other port to input measure amplifier to observe its reaction with ray input. When beam of light irradiated this eye, they can note a string impulse from micro electrode. The magnitude of impulse has direct ratio with the logarithm of light intensity. Each port of two electrodes was inserted into the adjacent neural fibrin of two small eyes, and the other port was linked to amplifier. They use beam of light with same intensity to irradiate this two small eyes, then they noted impulse from these two micro-electrodes. But this two output impulse frequency is lower than separated each other. This confirmed that when a sensitive cell brings excitement due to light stimulation, it can restrict conjoint sensitive cells. In other words, the output of each small eyes can reduce the function of adjacent small eyes output. Because this inhibition function is achieved by inhibition networks of each small vision neural fibrin, it is called lateral inhibition.[4][5]

B. Lateral inhibition models

By large numbers of electrophysiological experiment, Hartlein and his colleagues advanced a classical lateral inhibition model, as in (7).

\[ r_p = e_p + \sum_{j=1}^{n} k_{p,j}(r_j - r_p^0) \quad (7) \]

In this model, \( e_p \) is the input of \( p \) small eye, \( r_p \) is the output of \( p \) small eye, \( r_j \) is the output of \( j \) small eye, \( r_p^0 \) is the threshold which \( j \) effects on \( p \). \( k_{p,j} \) is the lateral inhibition coefficient which \( j \) effects on \( p \).

Besides Hartlein model, there are other models listed below.

\[ r_p = I_p \frac{k \cdot I_p}{\sum_{j=1}^{n} k_{p,j} I_j} \quad (8) \]

\[ r_p = \log \frac{I_p}{1 + \sum_{j=1}^{n} k_{p,j} I_j} \quad (9) \]

\[ r_p = \sum_{j=1}^{n} k_{p,j} I_j \quad (10) \]

![Figure 1. The compound eye of limulus](Image)
According to different classification criteria, lateral inhibition model can be divided into three categories. According to quantity of lateral inhibition in mathematical model depends on the output or input around the unit, it is divided into circulation model and acyclic model. According to inhibitory effect achieved through the combined effects of segregation or summation, it is divided into subtraction model and diffusent type model. Based on the relationship of these mathematical model is linear or non-linear, it can be divided into linear and nonlinear model.

C. Acyclic Lateral Inhibition Network Model

Based the models advanced by researchers, ALINM is established in this essay. Its one-dimensional expression as in (12).

$$r_p = e_p - \sum_{j=1}^{n} k_{pj} \times e_j$$  \hspace{1cm} (12)

In (12), $e_p$ is the input of $(p)$ small eye, $r_p$ is the output of $(p)$ small eye, $e_j$ is the input of $(j)$ small eye, $k_{pj}$ is the lateral inhibition modulus which $(j)$ effects on $(p)$.

Equation (12) is an one-dimensional, if the receptive field of this lateral inhibition model is supposed $1 \times 3$, it means only two adjacent units have mutual inhibition function. If lateral inhibition coefficient $k$ among each node is supposed equal, then the acyclic lateral inhibition model with six nodes is shown in Fig.2.

In Fig.2, black arrowhead means inhibition relation. $-k$ is multiplied on the basis of other input $e$, and then this result is added to input $e$ of this unit. As a result, this unit output $r$ can be obtained. The operation process as in (13).

$$\begin{align*}
    r_1 &= e_1 - k \times (e_0 + e_2) \\
    r_2 &= e_2 - k \times (e_1 + e_3) \\
    r_3 &= e_3 - k \times (e_2 + e_4) \\
    r_4 &= e_4 - k \times (e_3 + e_5) \\
    r_5 &= e_5 - k \times (e_4 + e_6) \\
    r_6 &= e_6 - k \times (e_5 + e_7)
\end{align*}$$  \hspace{1cm} (13)

In (3), $e_0$ and $e_7$ are the edge of linear unit from 1 to 6. If it has only process 6 units, $e_0$ and $e_7$ should be 0, which means unit 1 and 6 only inhibited by single unit, so the inhibition of this unit is less than other units. Because lateral inhibition modulus is negative, the output intensity is generally lower than input.

We use the calculation magnitude of circulation difference lateral inhibition model to express the advantage of ALINM. The equation of this model as in (14).

$$r_p = e_p + \sum_{j=1}^{n} k_{pj} \times r_j$$  \hspace{1cm} (14)

The inhibition field of this model is supposed $1 \times 3$, it means only neighboring units have inhibition effect. In (14), $e_p$ is input variable, $r_p$ and $r_j$ is output variable, $k_{pj}$ is inhibition modulus, this parameter between each units is supposed equivalent, the calculation process of this model is shown in Fig.3.

The equation of this model is given as in (15).

$$\begin{align*}
    r_1 &= e_1 - k \times (e_0 + r_2) \\
    r_2 &= e_2 - k \times (r_1 + r_3) \\
    r_3 &= e_3 - k \times (r_2 + r_4) \\
    r_4 &= e_4 - k \times (r_3 + r_5) \\
    r_5 &= e_5 - k \times (r_4 + r_6) \\
    r_6 &= e_6 - k \times (r_5 + r_1)
\end{align*}$$  \hspace{1cm} (15)

Equation (15) can be modified as in (16).

$$\begin{bmatrix}
    r_1 \\
    r_2 \\
    r_3 \\
    r_4 \\
    r_5 \\
    r_6
\end{bmatrix} = \begin{bmatrix}
    k & 1 & 0 & 0 & 0 & 0 \\
    0 & k & 1 & 0 & 0 & 0 \\
    0 & 0 & k & 1 & 0 & 0 \\
    0 & 0 & 0 & k & 1 & 0 \\
    0 & 0 & 0 & 0 & k & 1 \\
    0 & 0 & 0 & 0 & 0 & k
\end{bmatrix} \begin{bmatrix}
    e_0 \\
    e_1 \\
    e_2 \\
    e_3 \\
    e_4 \\
    e_5
\end{bmatrix}$$  \hspace{1cm} (16)

If there are only six units in processing, the value of $e_0$, $e_7$, $r_0$ and $r_7$ are 0, then (16) can be turned into (17).

$$\begin{bmatrix}
    r_1 \\
    r_2 \\
    r_3 \\
    r_4 \\
    r_5 \\
    r_6
\end{bmatrix} = \begin{bmatrix}
    k & 1 & 0 & 0 & 0 & 0 \\
    0 & k & 1 & 0 & 0 & 0 \\
    0 & 0 & k & 1 & 0 & 0 \\
    0 & 0 & 0 & k & 1 & 0 \\
    0 & 0 & 0 & 0 & k & 1 \\
    0 & 0 & 0 & 0 & 0 & k
\end{bmatrix} \begin{bmatrix}
    e_1 \\
    e_2 \\
    e_3 \\
    e_4 \\
    e_5 \\
    e_6
\end{bmatrix}$$  \hspace{1cm} (17)

It can be concluded from this expression that the calculation of circulation difference lateral inhibition model is great than ALINM, so ALINM can process input image faster than circulation difference lateral inhibition model.
D. Enhancement principle prove of ALINM

The essence of contrast enhancement was analyzed with two points of view in this section. On the one hand, unit intensity difference between fore-and-aft processing. Only two adjacent units relation is analyzed in this section.

The inputs of acyclic lateral inhibition model are supposed as $e_1$ and $e_2$, and the outputs are $r_1$ and $r_2$. The 2-input ALINM is given in (18).

$$
\begin{align*}
\begin{cases}
r_1 = e_1 - k_{21}e_2 \\
r_2 = e_2 - k_{12}e_1
\end{cases}
\end{align*}
\quad (18)
$$

In (18), it is supposed as $e_2 = \rho e_1$, $k_{21} = k_{12} = k > 0$, and $0 < k < \rho < 1$ . Equation (16) is modified and then given in (19).

$$
\begin{align*}
\begin{cases}
r_1 = (1-k_{21} \rho)e_1 \\
r_2 = (\rho - k_{12})e_1
\end{cases}
\end{align*}
\quad (19)
$$

The formula of (19) is divided, and then it is obtained in equation (18).

$$
\frac{r_1}{r_2} = \frac{1-k_{21} \rho}{\rho - k_{12}} = \frac{1-k \rho}{\rho - k} \quad (20)
$$

In (20), the output ratio of neural unit is increased after mutual function between lateral inhibition units. It means the gray contrast of image is enhanced.

On the other hand, two formulas of (18) are decreased, and then the equation is given in (21).

$$
\begin{align*}
r_1 - r_2 = (e_1 - e_2) - k_{21} e_2 + k_{12} e_1 \\
= (e_1 - e_2) \times (1 + k)
\end{align*}
\quad (21)
$$

Equation (21) is modified and then given in (22).

$$
r_1 - r_2 = \Delta r = \Delta e \times (1 + k) \quad (22)
$$

Because $1 + k > 1$, so $\Delta r > \Delta e$, the difference between two units is enhanced.

E. Transfer function of ALINM

The stable equation of (12) is modified in time domain style, and then given in (23).

$$
r(x, t) = e(x, t) - \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} k(x-x', t-t') e(x', t') dx' dt' \quad (23)
$$

In equation (23), $r(x, t)$ is the reaction of dimensional position $x$ and time $t$, $e(x, t)$ is stimulation, and $k(x-x', t-t')$ is the inhibition value that small eye at position $x'$ and time $t'$ put on another eyes at position $x$ and time $t$. The inhibition value of one cell to another in this model depends on stimulation of the first cell. Stimulation as the function of time is changeless, $r(x, t)$ and $e(x, t)$ are invariable for all parameters, so it can be written like $r(x)$ and $e(x)$, and equation of system is modified and given in (24).

$$
r(x) = e(x) - \int_{-\infty}^{\infty} k(x-x') e(x') dx' \quad (24)
$$

$k(x-x')$ in (24) is equivalent to $k_{ij}$ in (12). Fourier transform of (24) is given in (25).

$$
R(\omega) = \tilde{E}(\omega) - \tilde{E}(\omega) \tilde{K}(\omega) \quad (25)
$$

$R(\omega), \tilde{E}(\omega)$ and $\tilde{K}(\omega)$ are the Fourier transform of $r(x), e(x)$ and $k(x, \omega)$ is frequency.

The transfer function $T_k(\omega)$ of lateral inhibition network is given in (26).

$$
T_k(\omega) = 1 - \tilde{K}(\omega) \quad (26)
$$

IV. ALINM ALGORITHM

In order to introduce this algorithm, (12) is modified in two-dimensional and gray form, gray value of one cell $(m, n)$ in image is given in (27).

$$
r(m, n) = e_p(m, n) + \sum_{i=-M}^{M} \sum_{j=-N}^{N} k_{ij} e(m + i, n + j) \quad (27)
$$

In (27), $r(m, n)$ is gray value of spot $(m, n)$ after lateral inhibition processing, $e_p(m, n)$ is gray value of spot $(m, n)$ before lateral inhibition processing. $M \times N$ is the receptive field $K_{ij}$ is lateral Inhibition modulus of image gray value in position $(i, j)$ to object position. $(m+i, n+j)$ is gray value before lateral inhibition in space $M \times N$ centered in $(m, n)$ to cell $(m+i, n+j)$.

Every neural cell in plural vision system has relative stability and consistency with its lateral affiliation around neural cell and edge restriction without direction, so lateral inhibition modulus can be understood symmetrical around center. The selected central modulus is $k_0$, the modulus around center $k_j$, modulus out space $k_2$, modulus in space $7 \times 7$ is $k_j$, and (27) can be modified and given in (28).

$$
r(m, n) = e(m, n) + k_0 e(m, n) + k_j \sum_{i=-j}^{j} \sum_{j=-j}^{j} e(m+i, n+j) - I(m, n)
$$

$$
+ k_2 \sum_{i=-3}^{3} \sum_{j=-3}^{3} e(m+i, n+j) - \sum_{i=-1}^{1} \sum_{j=-1}^{1} e(m+i, n+j)
$$

$$
+ k_3 \sum_{i=-3}^{3} \sum_{j=-3}^{3} e(m+i, n+j) - \sum_{i=-2}^{2} \sum_{j=-2}^{2} e(m+i, n+j)
$$

The distribution of lateral inhibition modulus can be obtained by (29).

$$
K_i = \frac{1}{\sqrt{2\pi \sigma}} \exp \left( -\frac{d_i^2}{2\sigma^2} \right) \quad (29)
$$

In (29), $\sigma = 19.3$. $d_i$ is the distance between center cell and cell in $i$-dimension, $K_i$ ($i=0$-3) is the Lateral Inhibition modulus. $K_i$ is shown in (30).
From (28) and (29), we can get competitive modulus of lateral inhibition. Based on the definition of edge enhancement, setting a value $T$, and then image edge can be obtained by (31) finally.

$$I(m,n) = \begin{cases} 1 & r(m,n) \geq T \\ 0 & r(m,n) < T \end{cases}$$  \hspace{1cm} (31)

V. EXPERIMENT AND RESULTS

In order to improve the correctness and feasibility of localization algorithm, this experiment chose a blurry image from CCD is designed, it is shown in Fig.5. There are two important parameters that effect result of lateral inhibition result. One is the receptive field $M \times N$, the other is the distribution of lateral inhibition modulus, it is Gauss distribution, this distribution equation is given in (29), it has two parameters $\sigma$ and $k$. The results after lateral inhibition processing with different parameters are shown in Fig.4-8.

The size of the receptive field has a more significant impact to edge the results of enhancement. Since the side effect of the total space there, the center receptors inhibited the adjacent receptors more, the centre receptors are inhibited greater, highlighting the more obvious effects of the border, but access to the more broad outline of the image, the inhibitory effect of the noise is even more obvious, of course, the image some minor edge of the central plains will be missed out.

We also use two fuzzy images which were processed by ALINM, Fig.9 and Fig.11 are the initial fuzzy images, Fig.10 and Fig.12 are the images after processing by ALINM.
It can be confirmed from the experiment that ALINM with Gaussian distribution is easy to complete, and has good effect for image enhancement. Also it can be concluded from this experiment that the size of lateral inhibition receptive field has obvious effect to edge enhance processing result. Because there are space summation effect exist in lateral inhibition, so the more adjacent sensor which inhibit to central sensor, the more intense inhibition the central sensor received, and effect of extrusive frame is more obvious, image edge is broaden than before processing, even more inhibition effect to noise is more obvious. However, the tiny edge of primary image will be ignored, sometimes this information is so important for detection, and along with the receptive field increasing, the processing time lengthening obviously.

VI. LATERAL INHIBITION ELECTRO-MODEL

There are many hardware design methods to enhance image’s edge and improve image contrast, but most of this methods are taking linear processing to linear image signa. The image signal processed by lateral inhibition neural network is not linear, it is two-dimension video information, the advantage of this signal is parallel processing and can process in real time.

A. Design of in-phase input units

In-phase input units is shown in Fig.13, $R_f$ is minus feedback, this circuit work on linear area.

B. Design of inversed phase input units

In-phase input unit is shown in Fig.14, $R_f$ is minus feedback, this circuit work on linear area.

C. Simulation of one-dimension circuit

Inversed phase input unit is used to simulate 1×4 units, we use Multisim9.0 as a simulation tool, Net model is shown in Fig.15.

As there are only 4 units in this model, so input voltage of two borders are 0, the circuit of this model is shown in Fig.16.

The input voltage of each unit is 5V, The simulation result of this 1×4 inversed phase input circuit is shown in Table. I .

The lateral inhibition modulus resistance of 1×4 inversed phase input circuit is shown in Fig.17.

It can be concluded from Table. I that along with the increasing of $R_s$, the lateral inhibition effect is more obviously, when $R_s$ great than 6$k\Omega$, it will be over lateral inhibition, this is insignificant for lateral inhibition model.
In order to test lateral inhibition effect with different input voltage, we extend this circuit, the results after extending are shown in Table. and Table.

**TABLE II.**
**TEST RESULT OF EDGE EXTENDING**

<table>
<thead>
<tr>
<th>Test point</th>
<th>U10</th>
<th>U11</th>
<th>U12</th>
<th>U13</th>
<th>U14</th>
<th>U15</th>
<th>Uo1</th>
<th>Uo2</th>
<th>Uo3</th>
<th>Uo4</th>
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<td>-2.49</td>
<td>-2.49</td>
<td>-2.49</td>
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**TABLE III.**
**THE RESULT OF LATERAL INHIBITION EFFECT AFTER EDGE EXTENDING**

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**D. Simulation of two-dimension circuit**

Inversed phase input unit is used to simulate 4×4 units, we use Multisim9.0 as a simulation tool, the resistance of inhibition input and the lateral inhibition modulus resistance are shown in Fig.18, the circuit of this model is shown in Fig.19.

The output voltage processed by 4×4 inversed phase acyclic lateral inhibition model is shown in Table. IV, the lateral inhibition modulus resistance is 2kΩ and the resistance of inhibition input is 0.2.

**TABLE IV.**
**TEST RESULT OF 4×4 ACYCLIC MODEL**

<table>
<thead>
<tr>
<th>Test point</th>
<th>Uo1</th>
<th>Uo2</th>
<th>Uo3</th>
<th>Uo4</th>
<th>Rs</th>
</tr>
</thead>
<tbody>
<tr>
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<td>-1.99</td>
<td>-2.99</td>
<td></td>
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<td>-0.99</td>
<td>-0.99</td>
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<tr>
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<td>-0.99</td>
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</table>
VII. CONCLUSIONS

Image processing based on lateral inhibition theory has comprehensive biologic foundation. Its processing mechanism is introduced in this essay at first, then acyclic lateral inhibition network model (ALINM) is established. Based on this model, its enhancement principle is proved and its transfer function is analyzed, from this we can confirm that subtraction acyclic lateral inhibition networks enhance the edge of image, and image details lose can be avoided. However, this function effected by various factors, like style of model, the distribution of Lateral Inhibition modulus, and size of receptive field. The results of experiment show its effect. Different lateral inhibition model has different image’s contour enhancement effect. Despite it can be confirmed in theory that each kinds of lateral inhibition models has the effect of extruding frame and enhancing image’s contrast, but from the experiment result it can be concluded that ALINM with Guass distribution is easily realized and has great enhancement effect. The size of lateral inhibition receptive field has obvious effect to edge enhancement result. As the increasing of receptive field, the image’s contour can broaden than initial image, and it will has obvious inhibition effect to noise, but the small edge of initial image will be missed, and calculation time of lateral inhibition processing will be lengthened.

REFERENCES


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