MULTI-ADAPTIVE PARALLEL NEURO FUZZY INFERENCE SYSTEM FOR MEDICAL IMAGE DENOISING

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ABSTRACT - Normally, images are corrupted by impulse noise during acquisition and transmission over communication medium. As a result, noise removal and enhancement are essential in digital image processing. Since, the performances of subsequent processes in image processing are strictly dependent on the success of the image denoising. However, the complexity of this process is high due to the noise removal operator with the requirement of preserving useful information in the image during noise removal process. In previous researches, OFPTFLIS (Optimized Firefly based Parallel Type-2 Fuzzy Logic Filtering System) is introduced for removing the noise from the images. In this approach, image denoising is performed in optimized parallelized manner by using the firefly optimization and type-2 fuzzy logic system. However, the processing speed of the denoising process is less when multiple fuzzy rules are considered. Hence in this research, Multiple Adaptive Parallel Neuro Fuzzy Inference System (MAPNFIS) is proposed. This approach is introduced for improving the processing speed of denoising process with the multiple parameters. In addition, the fuzzy membership functions selection process is achieved adaptively. Here, Adaptive Fuzzy Inference System (AFIS) is hybridized with the Neural Networks (NN). It is a combination of both back propagation and the least square algorithms. When multiple membership functions are used, the performance of denoising is speeded up by computing the weighting factors of the rules. This system makes the utilization of a hybrid-learning rule for optimizing the fuzzy system parameters of a first order Sugeno system. Finally, the experimental results show that the proposed approach achieves better performance than the other approaches in terms of PSNR, MSE, MAE and computation time.

Keywords: Fuzzy rules, Image Denoising, Membership Function, Neural Network,

1. INTRODUCTION

One of the major issues faced while the acquiring and transmission of the images is image with impulse noise. Due to this unavoidable truth, generally the obtained or established digital image should be pre-processed through concerning a suitable filtering operator to the image to suppress the contaminate noise. If the noise is not filtered properly from the images then the performance of the image processing will get reduced significantly. Thus there are several methods and algorithms are improved to remove the impulse noise from the specified images efficiently. Also the researches focused on the design of operators for the restoration and enhancement of digital images which is used for identifying the impulse noise. Hence by using the effective and easy impulse noise removal operator remove the corrupted pixels from the images and increase the performance of image processing.

2. RELATED WORKS

In the previous research, the Parallel Fuzzy Inference System (PFIS) introduced for image denoising. In this method, the generated fuzzy inference rules are distributed to the nodes for parallel execution process. The inference rules are processed concurrently and compute the weighted average of the individual rule. So, the time complexity is reduced by using the Parallel Fuzzy Inference System. The work is divided as three phases: (1) Generation of fuzzy set based on distribution of fuzzy rules. (2) Defuzzification (3) Detection of impulse noise and Classification process

In this method, the input training images are given to the sub detector. The 3-by-3 pixel filtering window is used in every color band of the noisy input image one pixel at a time. In every filtering window, the appropriate pixels of the filtering window denote the appropriate neighborhoods of the center pixel are given to both the sub detectors and also noise filter. The sub detectors process the input and the inference rules are generated. The generated fuzzy inference rules are distributed to the nodes for simultaneous execution of the rules. The inference rules are processed in parallel manner and produce the type 1 fuzzy sets with less processing time. The output of the sub detectors are given to the two defuzzifiers. The defuzzifiers convert the type-1 interval fuzzy set into scalar values. The two scalar values from the defuzzifiers are converted into single value by using the postprocessor and it finds whether the pixel is noisy or normal. If the pixel is normal, center pixel of the filtering window is directly copied to the output image. If the pixel is noisy, the noise filter output is copied to the output image.

The preceding research has issue with selection of optimal parameters which affects the image denoising process. Hence to overcome those problems in this research enhance the concept of firefly optimized Parallel fuzzy inference (FOPFI) system. This approach is focused on the selection of suitable structure of membership functions with optimal parameters.

The firefly optimized Parallel fuzzy inference system involves discovering the optimal values of the parameters along with membership functions. The application of optimization algorithm for parallel fuzzy inference model identification involves a number of important considerations. The initial process in applying such an algorithm is to describe solution space (ranges of parameters to be optimized), a set of constraints and the fitness function. Another significant consideration is the solution encoding i.e. to represent a parallel fuzzy inference system by a firefly (set of fireflies represent a population). Each firefly represents a fuzzy system which consists of two parts: one represents membership functions of antecedents and consequents and second part represents rule-base. It is also suggested to modify the membership functions and rule-base simultaneously, since these are codependent in a fuzzy inference system. The generated fuzzy inference system uses the membership function and in order to optimize the membership function this method is combined with firefly algorithm.

To improve the fast denoising process in this research suggested Multi adaptive parallel neuro-fuzzy inference (MAPNFI) system. Preceding research also has addressed the issue which is rules for fuzzy memberships selection is not decided adaptively. Hence to handle this issues Multi adaptive parallel neuro-fuzzy inference system introduced in this work. Initially the feature extraction is done by automatically which removes unnecessary pixels from the specified images. Then a neuro-fuzzy model called multiple adaptive parallel neuro-fuzzy inference system is used for recognition purpose.

The multiple adaptive parallel neuro-fuzzy inference system contains a set of adaptive neuro-fuzzy inference system models which are arranged in parallel combination to produce a model with multi-input-multi output structure. Multi adaptive parallel neuro-fuzzy inference system is used for increasing the recognition process along with multiple optimized parameters. By using this method we can obtain the multiple optimized outputs with improvements in effective as well as fast denoising.

3. MULTI ADAPTIVE PARALLEL NEURO FUZZY INFERENCE SYSTEM (MAPNFIS) BASED IMAGE DENOISING

In this section, the proposed MAPNFIS based impulse noise removal in the image processing. Initially, the acquired images are categorized into training and testing images. The training images are given to the sub detector. Also, 3×3 filtering window is used in each color band of noisy image pixels at a given time.

In addition, the fuzzy inference rules are generated and distributed to the nodes in parallelized manner based on the PFIS. If multiple fuzzy parameters are used, then neural network is applied for deciding the image pixel whether it is noisy or noise-free pixel. The hybrid version of Neuro Fuzzy system is explained in below section.

3.1 Computation of Fuzzy Membership Function

The generation of fuzzy rules and distributed to the nodes based on the scattered principle in parallel manner is described in previous research. The MAPNFIS is built for enhancing the process of removing the impulse noise from the images. It is a first order Sugeno type fuzzy system with three inputs and one output. The most popular nonlinear modeling tool is Sugeno-type fuzzy system since they are very suitable for tuning process by optimization and consists of polynomial type output membership functions for simplifying the defuzzification process[5]. MAPNFIS consists of five layers which are shown in Figure 1.

The inputs are denoted as X_1, X_2, X_3 and the output is represented as Y. The functions of the five layers are described in below:

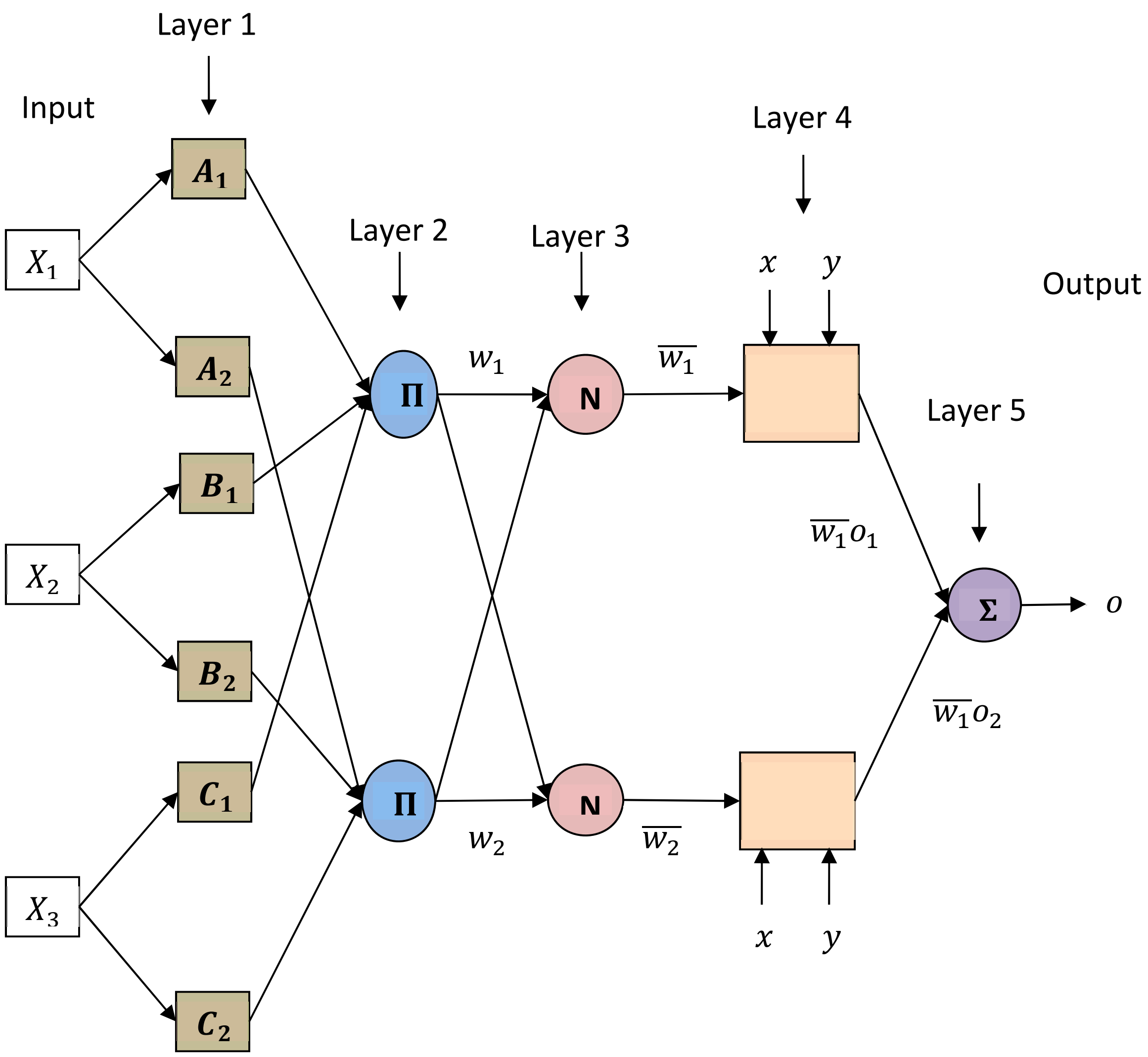

Fig. 1 Architectural Layers of MAPNFIS

Layer 1 (Input Layer): The initial layer of MAPNFIS has some nodes as adaptive nodes. Each node in this layer is square node with a node function i.e., membership value [2]. In this layer fuzzy membership degree is computed based on the given inputs and its output is input membership degree which is given in following equation:

$$Y_{1,i} = \mu_{A_{ij}}(X_1), for\ i = 1\ ,2; j = 1,2,3 \qquad (3.1)$$

$$Y_{1,i} = \mu_{B_{ij}}(X_2), for\ i = 1,2; j = 1,2,3 \qquad (3.2)$$

$$Y_{1,i} = \mu_{C_{ij}}(X_3), for\ i = 1,2; j = 1,2,3 \qquad (3.3)$$

Where $\mu_{A_{ij}}(X_i) = exp\left(\frac{-(X_i - m_{ij})^2}{2\sigma_{ij}^2}\right),\ for\ i = 1,2; j = 1,2,3$ (3.4)

In above equations, $\mu_{A_{ij}}, \mu_{B_{ij}}\ and\ \mu_{C_{ij}}$ are referred as the degree of membership functions of $A_{ij}, B_{ij}\ and\ C_{ij}$ which are defined as the linguistic labels such as fuzzy sets associated with i^{th} node function and these functions obey the Gaussian distribution. The mean and standard value for the membership function is represented as m_{ij} and σ_{ij}.

Layer 2 (Fuzzy Input Membership Function): Each node in this layer is fixed. Neurons in this layer show the fuzzy membership function for existence input in system. Each node output represents the firing strength of a rule and the output is given as follows:

$$Y_{2,i} = w_i = \quad \mu_{A_{ij}}(X_1)\mu_{B_{ij}}(X_2)\mu_{C_{ij}}(X_3), for\ i = 1,2; j = 1,2,3 \qquad (3.5)$$

Layer 3 (Fuzzy Rules): In this layer, the nodes are fixed and doing the role of normalization of firing strength of the layer 2. Here, i^{th} node computes the ratio of i^{th} rule's firing strength to the sum of all firing strengths. The obtained output is denoted as follows:

$Y_{3,i} = \overline{w_i} = \frac{w_i}{w_1+w_2}, for\ i = 1,2$ (3.6)

Layer 4 (Fuzzy Output Membership Function): In this layer, the nodes are adaptive. Each node in this layer is a square node with the node function and the output of this layer is denoted as follows:

$Y_{4,i} = \overline{w_i}o_i = \overline{w_i}(c_{i1}X_1 + c_{i2}X_2 + c_{i3}X_3 + c_{i4}), for\ i = 1,2$ (3.7)

In equation (3.7), $c_{i1}, c_{i2}, c_{i3}\ and\ c_{i4}$ are referred as the output parameters.

Layer 5 (Output Layer): It has the fixed node which is used for determining the sum of inputs on it and the output of this layer is given as follows:

$Y_{5,i} = \sum_i \overline{w_i}o_i = \frac{\sum_i w_i o_i}{\sum_i w_i}, for\ i = 1,2$ (3.8)

The above equation provides the overall output of MAPNFIS efficiently. Once this process is completed for training images by using N number of fuzzy rules, testing images are analyzed by using this process and classify the pixel whether it is noisy or noise-free pixel by using median filter.

4. EXPERIMENTAL RESULTS

In this section, the performance effectiveness of the proposed Multiple Adaptive Parallel Neuro Fuzzy Inference System (MAPNFIS) is evaluated and compared with the Optimized Firefly-based Parallel Type-2 Fuzzy Logic Inference System (OFPTFLIS) based Impulse detector in terms of mean squared error, false classification ratio and processing time, peak signal-to-noise ratio. MATLAB simulation environment is used to prove the improvement and the successful execution of the environment in case of presence of more noisy images. In the experiments, the noisy analysis medical pictures are non inheritable by contaminating a given testing picture with an impulse noise of given noise density. Numerous noise density values are used such are 25%, 50% and 75% which indicates the low, medium and high noise densities, correspondingly.

4.1 Mean Squared Error

Mean Squared Error (MSE) is defined as follows:

$MSE = \frac{1}{LC}\sum_{l=1}^{L}\sum_{c=1}^{C}(s[l,c] - \gamma[l,c])^2$

In above equation, $s[l,c]$ and $\gamma[l,c]$ denotes the luminance value of the pixel at line l and column c of one of the three color bands of the original and the restored versions of a corrupted test image correspondingly. The MSE is valid for the gray-scale images. But the testing images are color images. So, the MSE computation is performed for three times, one for each color bands and the three resulting MSE values are averaged to acquire the particular MSE value for the image.

The MSE comparison for the existing and proposed system is shown in Table 1. If the noise density is 75%, the MSE is 51 in the existing FOPFIS method and 46 in the proposed method.

Table 1 Comparison of MSE

Noise Density	FOPFIS	MAPNFIS
25%	37	32
50%	45	41
75%	51	46

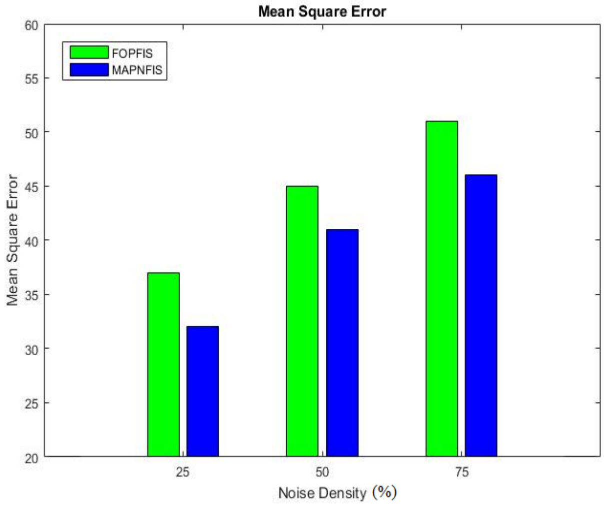

Fig. 2 Comparison of MSE

Figure 2 shows that the comparison of MSE for existing and proposed system. In x-axis, the noise densities are taken in %. In y-axis, MSE values are considered. If the noise density is 25%, then the MSE of FOPFIS and proposed MAPNFIS are 37 and 32 respectively. When the noise density is 50%, the corresponding MSE value of FOPFIS and proposed MAPNFIS are 45 and 41 respectively. Also, if the noise density is 75%, then the MSE value of FOPFIS and proposed MAPNFIS are 51 and 46 correspondingly. From the analysis, it is observed that the proposed MAPNFIS has less mean square error value compared with the existing method.

4.2 False Classification Ratio

False classification ratio is defined as follows:

$$FCR = \frac{N_F}{N_T} \times 100$$

Where N_F denotes the falsely classified pixels of the input image and N_T represents the total number of pixels. The FCR comparison for the existing and proposed system is shown in Table 5.2. If the noise density is 75%, the FCR is 4.2% in the existing FOPFIS method and 3.6% in the proposed method.

Table 2 Comparison of FCR (%)

Noise Density	FOPFIS	MAPNFIS
25%	1.9	1.5
50%	3.2	2.8
75%	4.2	3.6

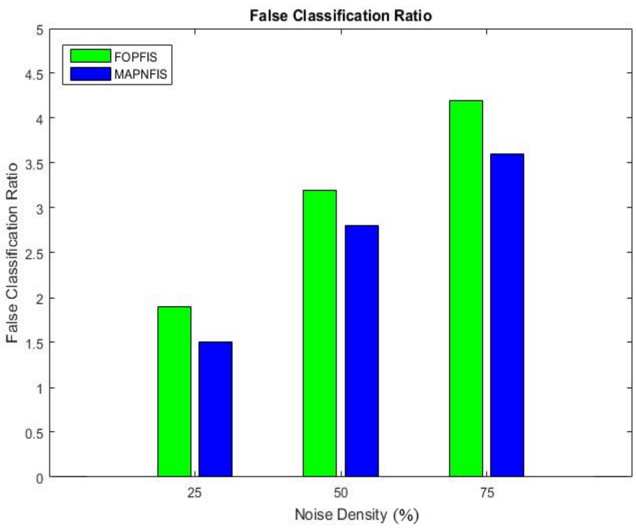

Fig. 3 Comparison of FCR

Figure 3 shows that the comparison of FCR for existing and proposed system. In x-axis, the noise densities are taken in %. In y-axis, FCR values are considered in %. If the noise density is 25%, then the FCR of FOPFIS and proposed MAPNFIS are 1.9% and 1.5% respectively. When the noise density is 50%, the corresponding FCR value of FOPFIS and proposed MAPNFIS are 3.2% and 2.8% respectively. Also, if the noise density is 75%, then the FCR value of FOPFIS and proposed MAPNFIS are 4.2% and 3.6% correspondingly. From the analysis, it is observed that the proposed MAPNFIS has less false classification ratio compared with the existing method.

4.3 Computation Time

Computation time is defined as the time taken for processing the images and filters the noise.

The comparison of computation time for the existing and proposed system is shown in Table 3. If the noise density is 75%, the computation time is 2.47ms in the existing FOPFIS method and 1.91ms in the proposed method.

Table 3 Comparison of Computation Time (ms)

Noise Density	FOPFIS	MAPNFIS
25%	2.04	1.51
50%	3.35	2.5
75%	2.47	1.91

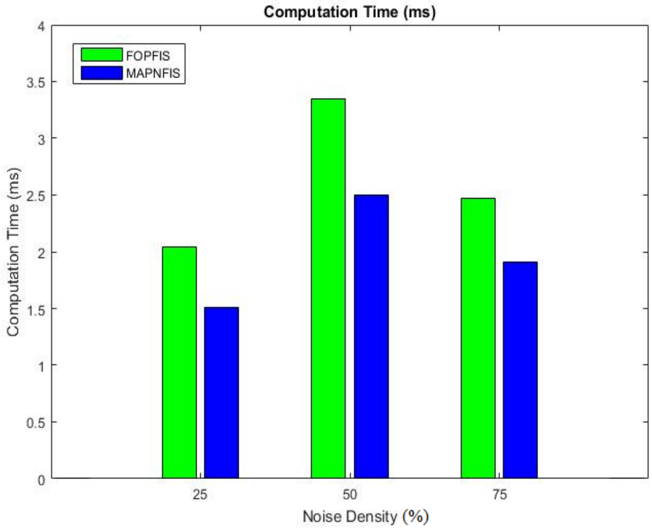

Fig. 4 Comparison of Computation Time

Figure 4 shows that the comparison of computation time for existing and proposed system. In x-axis, the noise densities are taken in %. In y-axis, computation time values are considered in milliseconds. If the noise density is 25%, then the computation time of FOPFIS and proposed MAPNFIS are 2.04ms and 1.51ms respectively. When the noise density is 50%, the corresponding computation time of FOPFIS and proposed MAPNFIS are 3.35ms and 2.5ms respectively. Also, if the noise density is 75%, then the computation time of FOPFIS and proposed MAPNFIS are 2.47ms and 1.91ms correspondingly. From the analysis, it is observed that the proposed MAPNFIS has less computation time compared with the existing method.

4.4 Peak Signal-to-Noise Ratio

Peak signal-to-noise ratio (PSNR) is used to represent the index of media quality analysis and substitutes the average MSE of frames in the PSNR computing equation to obtain the PSNR value of the media segment and it is expressed as follows:

$$\mathrm{PSNR} = 20 \times \log_{10}\left(\frac{255}{\sqrt{\mathrm{MSE}}}\right)$$

The PSNR comparison for the existing and proposed system is shown in Table 4. If the noise density is 75%, the PSNR is 86% in the existing FOPFIS method and 90% in the proposed method.

Table 4 Comparison of PSNR (%)

Noise Density	FOPFIS	MAPNFIS
25%	36	40
50%	53	56
75%	86	90

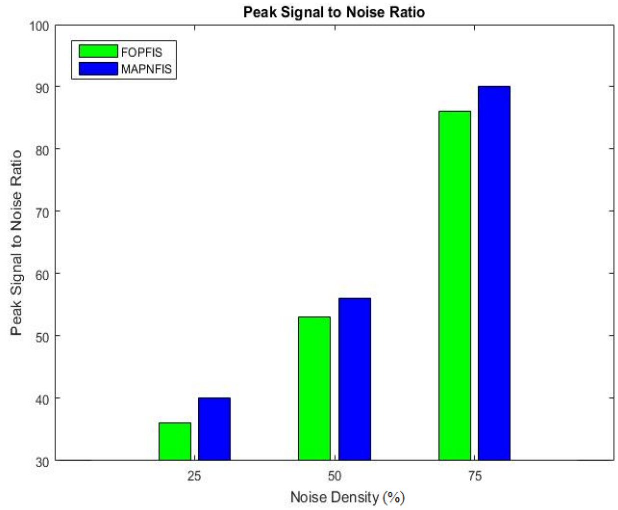

Fig. 5 Comparison of PSNR

Figure 5 shows that the comparison of PSNR for existing and proposed system. In x-axis, the noise densities are taken in %. In y-axis, PSNR values are considered in %. If the noise density is 25%, then the PSNR of FOPFIS and proposed MAPNFIS are 36% and 40% respectively. When the noise density is 50%, the corresponding PSNR value of FOPFIS and proposed MAPNFIS are 53% and 56% respectively. Also, if the noise density is 75%, then the PSNR value of FOPFIS and proposed MAPNFIS are 86% and 90% correspondingly. From the analysis, it is observed that the proposed MAPNFIS has less peak signal-to-noise ratio compared with the existing method.

CONCLUSION

In this paper, Multiple Adaptive Parallel Neuro Fuzzy Inference System (MAPNFIS) is introduced for improving the noise removing process in image processing. In this method, adaptive Neuro-fuzzy system is used with consideration of multiple parameters. The major objective of this method is improving the speed ability of the image denoising performance with the combination of neural network and fuzzy inference system. It enhances the selection process of membership functions for finding the noisy and noise-free pixels in the images effectively. Finally, the experimental results prove that the proposed MAPNFIS has better performance compared to the other image denoising approaches in terms of MSE, PSNR, MAE and computation time.

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