IFPI control sums up changing nominal gains of the existing PI controller by referring to fuzzy matrices, i.e. a skillfully designed look-up table. The main advantage of the proposed technique is that it can be implemented quite easily by adding a microprocessor component that carries out the extra computation to the existing hardware PI controllers.

To obtain the optimal gains of controllers, the genetic algorithm, a general optimization method, is used, and the resulting overshoot of rotor speed and exhaust temperature under proposed fuzzy PI controller are considerably decreased. As future work, we plan to investigate the design of the fuzzy compensator to improve the performance of the temperature controller.

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Application of Fast Haar Transform and Concurrent Learning to Tool-Breakage Detection in Milling

H. K. Tönshoff, Xiaoli Li, and C. Lapp

***Abstract*—In this paper, an effective monitoring approach for manufacturing processing by combining the in-place fast Haar transform and the concurrent learning is described and applied to detect tool flute breakage during end milling by sensing the feed-motor current signatures. The application procedure and the effectiveness of the proposed method have been delineated by case studies; the results indicate that the proposed approach possessed an excellent potential application to tool breakage detection in milling.**

***Index Terms*—Concurrent learning (CL), end milling, fast Haar transform (FHT), finite-impulse response (FIR) median hybrid filters, recursive, tool-flute breakage.**

I. INTRODUCTION

Immediate response to tool failure during end milling may prevent the workpiece and machine tools from excessive damage. The most frequent approach taken to end the milling process monitoring is to attach sensors to the machine or process and then monitor the signals obtained from these sensors. Research to date has presented investigation on cutting force, acoustic emission (AE), vibration/acceleration, and motor current/power [1] to detect tool failure during end milling. In this paper, we proposed a new approach to monitor tool failure, especially focused on tool flute breakage monitoring during end milling.

Tool-flute-breakage detection based on cutting force has been done in several research studies [2]. Cutting force is usually measured by using a dynamometer mounted on machining worktable, or mounted on the tool holder. However, the fixation of dynamometer and its cost are two main problems for the application of the method. AE is another important method. It was very successfully applied to tool condition monitoring in signal-point cutting, like turning operations [3]–[5]. More details can be found in [14]. Its application to end milling, however, involves some disadvantages, such as the sensitivity for cutting conditions, the fixation of the AE sensor and the complexity of AE signal processing. Vibration analysis is also a valuable method, which was widely used for tool-condition monitoring, especially for tool-wear monitoring and tool-failure prediction [6]. However, in the context of tool-condition monitoring in end milling, its application is somewhat limited by the nature of an end milling process as well as AE-based method.

Spindle or feed-motor current-based tool-breakage monitoring systems have been presented in the end milling operations to overcome the disadvantages of cutting force and AE/vibration-based methods, described in [7]–[10]. To monitor tool failure successfully through the motor current signals, an appropriate signal-processing algorithm is very important because the motor current signals do not indicate more obviously cutting tool condition than cutting force, AE and vibration signals. To meet the need of tool breakage monitoring by using motor-current, we apply recursive in-place growing FIR-median hybrid filters,

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in-place fast Haar transform (IP_FHT) and concurrent learning (CL) to construct a new algorithm for detecting tool flute breakage during end milling.

II. METHODS

A. IP_FHT

Haar basic transformation expresses the approximating function $\hat{f}$ with wavelets by replacing an adjacent pair of steps via one wider step and one wavelet. The wider step measures the average of the initial pair of steps, while the wavelet formed by two alternating steps, measures the difference of the initial pair of steps. The shifted and dilated wavelet $\psi_{(u,w)}$ is defined by the midpoint $v = (u + w)/2$

$$\psi_{[u,w)} = \begin{cases} 1, & \text{if } u \leq r < v \\ -1, & \text{if } v \leq r < w. \end{cases} \quad (1)$$

Again, the sum and the difference of the narrower steps give a wider step and a wavelet

$$\begin{cases} \varphi_{[u,w)} = \varphi_{[u,v)} + \varphi_{[v,w)} \\ \psi_{[u,w)} = \varphi_{[u,v)} - \varphi_{[v,w)} \end{cases} \quad (2)$$

yields

$$\begin{cases} \varphi_{[u,v)} = \frac{1}{2}\left(\varphi_{[u,w)} + \psi_{[u,w)}\right) \\ \varphi_{[v,w)} = \frac{1}{2}\left(\varphi_{[u,w)} - \psi_{[u,w)}\right). \end{cases} \quad (3)$$

The shifted and dilated basic transform described are applied to all the consecutive pairs of signals. To analyze a signal in terms of wavelets, the fast Haar wavelet transform begins with the initialization of an array with 2^n entries, and then proceeds with n iterations of the baxsic transform. The procedure of fast Haar wavelet transform is as follows:

1) Initialization. Initialization consists of establishing a one-dimensional array $\overline{\mathbf{a}}^{(n)}$

$$\overline{\mathbf{a}}^{(n)} = \left(a_0^{(n)}, \ldots, a_j^{(n)}, \ldots, a_{2^n-1}^{(n)}\right) = (S_0, \ldots, S_j, \ldots, S_{2^n-1})$$

with a total number of sample-value integral power of two 2^n, as indicated by the $\text{superscript}^{(n)}$.

2) Sweep. The lth sweep of the basic transform begins with an array of $2^{n-(l-1)}$ values

$$\overline{\mathbf{a}}^{(n-[l-1])} = \left(a_0^{(n-[l-1])}, \ldots, a_{2^{n-(l-1)}-1}^{(n-[l-1])}\right)$$

and applies the basic transform to each pair $(a_{2k}^{(n-[l-1])}, a_{2k+1}^{(n-[l-1])})$, which gives two new wavelet coefficients

$$a_k^{(n-1)} = \frac{a_{2k}^{(n-[l-1])} + a_{2k+1}^{(n-[l-1])}}{2}$$
$$c_k^{(n-1)} = \frac{a_{2k}^{(n-[l-1])} - a_{2k+1}^{(n-[l-1])}}{2}.$$

These $2^{(n-l)}$ pairs of new coefficients represent the result of the lth sweep, a result can be reassembled into two arrays

$$\overline{\mathbf{a}}^{(n-l)} = \left(a_0^{(n-l)}, \ldots, a_{2^{n-l}-1}^{(n-l)}\right)$$
$$\overline{\mathbf{c}}^{(n-1)} = \left(c_0^{(n-l)}, \ldots, c_{2^{n-l}-1}^{(n-l)}\right)$$

Therefore, the presentation of all the steps of the fast Haar wavelet transform requires additional arrays at each sweep, and it assumes that the whole sample is known at the start of the algorithm. However, some applications require real-time processing as the signal proceeds, and do not allow sufficient space for additional arrays at each sweep. The IP_FHT [11] is able to solve the two problems, lack of space, or time. For each pair $[a_{2k}^{(n-[l-1])}$ and $a_{2k+1}^{(n-[l-1])}]$ in the in-place fast wavelet transform, instead of placing its results in two additional arrays, the lth sweep of the in-place transform merely replaces the pair $[a_{2k}^{(n-[l-1])}$ and $a_{2k+1}^{(n-[l-1])}]$ by the new entries $[a_k^{(n-l)}$ and $c_k^{(n-l)}]$.

Clearly, the IP_FHT differs from the FHT only in its indexing scheme, but it does not require additional arrays at each sweep; so, the lack of space and time problems have a solution in the in-place algorithm.

B. CL

The CL approach is useful for data processing because it can continuously learn without interruption, and it can calculate input-output functions at the same time [12]. If a fixed number n of samples values is considered, which are represented as an array $X, X = [x_1, x_2, \ldots, x_n]$. A standard statistical approach is used to compute the mean and variance of the samples as follows:

$$\mu = \frac{1}{\sum w_i} \sum_{i=1}^{n} w_i x_i \quad \text{and} \quad v = \frac{1}{\sum w_i} \sum_{i=1}^{n} w_i (x_i - \mu)^2 \quad (4)$$

where w_i is weight value for each set of measurement. CL formulas are based on recursive updates of mean and variables of the previous samples for one univariate case. The CL mean and variance are updated at each point $n(n = 1, 2, \ldots)$ as follows:

$$\mu(n) = \frac{(l(n)x(n) + \mu(n-1))}{(1 + l(n))} \quad (5)$$

and

$$\nu(n) = \frac{\left(l(n)\left(x(n) - \widehat{x}(n)\right)^2 + v(n-1)\right)}{(1 + l(n))} \quad (6)$$

where $l(n)$ and $\widehat{x}(n)$ are called the current learning weight and predicted value, respectively

$$l(n) = \frac{w(n)}{\sum_{i=1}^{n-1} w(i)} \quad \text{and} \quad \widehat{x}(n) = \mu(n-1). \quad (7)$$

Therefore, the tolerance band function is computed by

$$(\underline{x}(n), \overline{x}(n)) = \left(\widehat{x}(n) - c\sqrt{\nu(n)}, \widehat{x}(n) + c\sqrt{\nu}(n)\right) \quad (8)$$

The tolerance band will be used as the threshold for detecting the tool breakage during end milling. Once the monitoring feature is outside of the tolerance band, the system is considered to enter an abnormal state. Advantages of CL methods are: 1) the CL can adjust their prediction and monitoring equations in real time. Therefore, they can be adapted to changing conditions much more quickly than off-line methods, and they require much less data effort than off-line analysis; 2) CL can assign differential learning weights in order to alter the impact of recently gathered data on learning and monitoring in comparison to the older data; 3) CL does not require specialized preprogramming and keeps up with data arriving at very high rates.

III. TOOL-BREAKAGE MONITORING DURING END MILLING

An experiment was performed on a CNC Vertical Machining Centre (Mazak AJV 25/405) with the ac permanent magnet synchronous motors. The experimental set up can be found in [13]. The test was performed under dry conditions in down milling mode, the sampling frequency was set to 1 KHz. Additionally, the maximum tooth frequency used in the tests should be less than 67 Hz, and is determined by the bandwidth of the servo system.

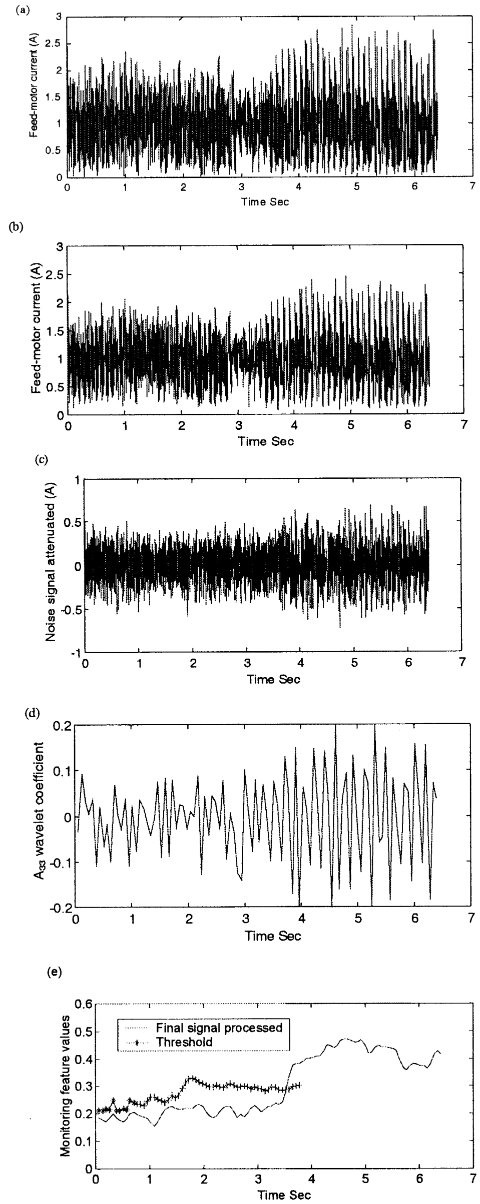

Fig. 1. (a) Feed-motor current signals from normal tool condition to tool flute breakage in end milling. (b) Preprocessed signal. (c) Signal-attenuated noise. (d) Coefficient a_{33} of wavelet transform. (e) Final monitoring features and the float thresholds. Tool/workpiece material: HSS/45# steel; spindle speed: 600 r/m, radial depth of cut: 2 mm, axial depth of cut: 4 mm, feed speed: 120 mm/min; cutter diameter: 8 mm, cutter flute: 4.

Fig. 1(a) displays a segmentation of a feed-motor current signal that contains a tool flute breakage during end milling, noted that the tool breakage occurred without artificial action. This breakage appears at about 3 s in Fig. 1(a). To eliminate the effects of unexpected noise, a recursive in place growing finite impulse response (FIR) median hybrid (RIPG_FMH) filter [14] is used to process the motor current signals before it is applied to detect the tool flute breakage during end milling. The (RIPG_FMH) filter with three-level median operation and increasing averaging substructures of lengths 1, 2, and 3 is designed. The filter is applied to the signals in Fig. 1(a), the result is shown in Fig. 1(b). The noise attenuated is shown in Fig. 1(c). Fig. 1 shows that the filter can preserve the shape of the original motor current signal and attenuate the noise involved in the original signal in real time, the mean of signal-to-noise (S/N) ratio is 24.8 dB. As a result, the preprocessed signal is very useful for further extraction the monitoring features form the motor current signal. In addition, the in-place growing algorithm provides a much shorter signal delay than the other filters [14]. Then, the Haar transform decomposes the feed-motor current signals provided in Fig. 1(b). We found that the wavelet coefficients a_{33} was much better to indicate the changes of the system, and it is shown in Fig. 1(d) It can be seen that the amplitude of the coefficient alternates at a higher range when tool flute breakage occurs after 3 seconds.

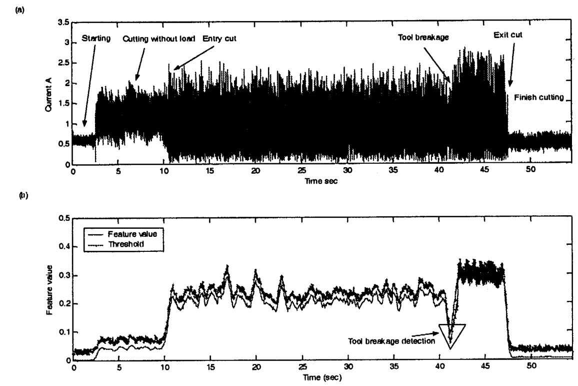

Fig. 2. Illustration of a complete test. Tool/workpiece material: HSS/45# steel; spindle speed: 900 r/m, radial depth of cut: 2 mm, axial depth of cut: 4 mm, feed speed: 100 mm/min; cutter diameter: 6 mm, cutter flute: 4.

For further extracting the monitoring features from the wavelet coefficient a_{33}, a simple high-pass and rms filter are designed to further treat with the signals. The high-pass filter used is a simple discrete second derivative approximation, and the output $z(n)$ is given by

$$z(n) = x(n-1) - 2x(n) + x(n+1) \tag{9}$$

rms filter is used to envelop the $z(n)$ signal, and output is $w(n)$. This can be achieved by a local rms operator applied on $z(n)$ over a sliding window of length $2N+1$, i.e,

$$w(n) = \sqrt{\frac{1}{2N+1}\sum_{i=-N}^{N} z(n+i)^2} \tag{10}$$

where the length $2N+1$ of the averaging window is not very critical, but it should be large enough to include at least one cycle of the impulsive oscillations (such as $N = 5 \sim 7$). For the mentioned example, $N = 5$ is selected. The resulting signal extracted from feed-motor current under application of the described filters is shown in Fig. 1(e). The change due to tool flute breakage is remarkable between second 3 and 4, clearly.

An appropriate threshold to detect the tool-flute breakage based on the monitored feature in real time has to be set. Considering the effects of changes of cutting conditions, a float threshold based on CL is developed. This is made in order to detect the flute breakage based on the monitoring feature series during end milling. According to the description of CL, the tolerance band can be computed in real time without off-line data analysis. The upper limit of tolerance band can be taken as a float threshold for detecting the tool condition in real time during end milling. In this paper, the sample-based fact weights are $w_n = [1\ 1\ 1\ 2\ 2\ 2\ 4\ 4\ 4]$ the learning weight can be computed by (18). The float threshold based on CL is shown in Fig. 1(e). As a result, the tool flute breakage can be effectively detected by comparing the monitoring feeatures with the thresholds in real time. Since many changes occur over the life of the tool, a complete test and how the monitoring worked over the entire test is shown Fig. 2. Fig. 2(a) plots the feed motor current, including motor run, cutting without load, entry

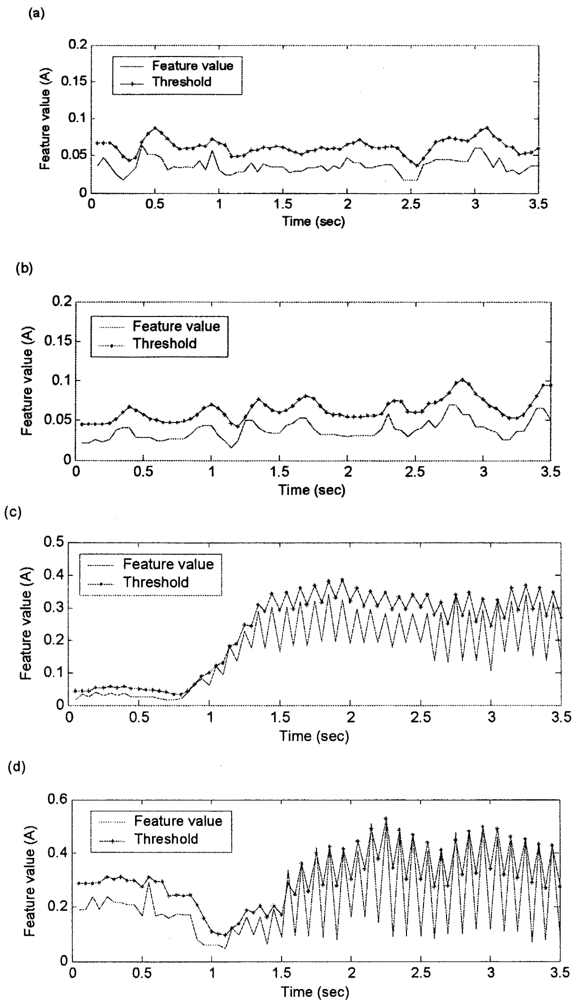

Fig. 3. Cut test in end milling. Entry and exit cut: tool/workpiece material: $\mathrm{HSS}/45^{\#}$ steel; spindle speed: 900 r/m, radial depth of cut: 2 mm, axial depth of cut: 4 mm, feed speed: 120 mm/min; cutter diameter: 8 mm, cutter flute: (a) Processed result of entry cut. (b) Processed result of exit cut. Flute breakage on entry cut /exit cut: spindle speed: 600 r/m, radial depth of cut: 4 mm, axial depth of cut: 4 mm, feed speed: 90 mm/min; cutter diameter: 6 mm, cutter flute: 4. (c) Processed results of one flute breakage during entry cut.(d) Processed results of two flutes breakage during exit cut.

cut, cutting, tool breakage (41.5 s), exit cut, and finish cutting. Fig. 2(b) shows the feature values and threshold values, the tool breakage can successfully be detected at the second 41–42, and the method does not provide false indications of failure.

To validate this approach, we implemented the detection algorithm to some special experiments as well. These examples include the entry/exit cuts, flute breakage on entry/exit cut and the effects of cutting parameters. The details of these experiments can be found in [13].

For the entry/exit cut test, Fig. 3(a) and (b) shows a plot of the processed feed-motor current signals corresponding to the float thresholds, respectively. As can be seen from the figures, all of the processed feed-motor current signals are well under the detection limits, thus demonstrating the *robustness* of the algorithm to entry, exit, and runout in milling. The flute breakage of some cutters in end milling usually occours on entry / exit cut. Fig. 3(c) is a plot of the detection results when cutter entries in the workpeice. Fig. 3(d) is a plot of the dection of cutter broken upon exit from the workpeice, two flutes of the cutting tools are broken for the event. For the two cases, the flute breakge can been sucsessfully detected by the detection algorithm through the com-

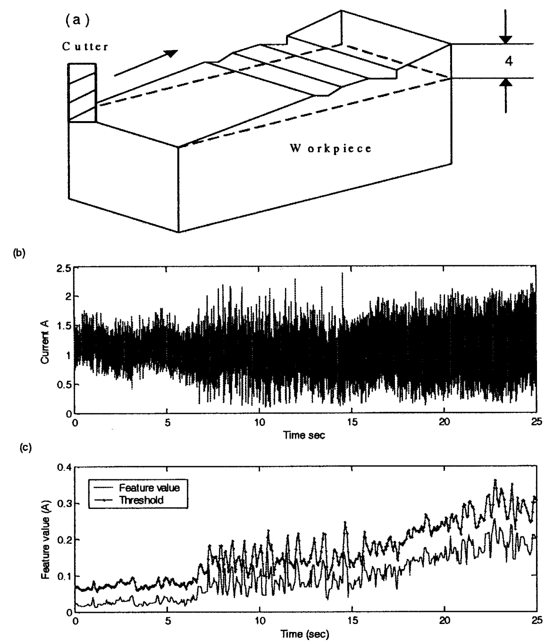

Fig. 4. Feed-motor current signals when cutting irregular workpiece. Tool/workpiece material: $\mathrm{HSS}/45^{\#}$ steel; spindle speed: 900 r/m, radial depth of cut: 4 mm, axial depth of cut: 0–4 mm, feed speed of cut: 120 mm/min; cutter diameter: 6 mm, cutter flute: 4. (a) Workpiece. (b) Feed-motor current signal. (c) Processed results of the feed-motor current.

parision between the processed current signals and the float threshold. The final tests are to verify the insensitivity of the algorithm of flute breakage detection to the changes of cutting parameters for end milli ng. The typical workpieces, which results in changes of axial depth of cut, are shown in Fig. 4(a). The processed result of the feed-motor current is shown in Fig. 4(b) correspondingly. From the result, the monitoring feature of the feed-motor current is insensitive to the change of cutting parameters during end milling.

The results of these examples showed that the detection algorithm could be effective to these different cases. Additionally, although all experiments were limited on end milling operations, we believe that the approach can be applied to other operation. Especially, the IP_FHT and the threshold settings based on the CL can be implemented for other monitoring systems.

IV. Conclusions

In this paper, a method is presented, which integrates the RIPG-FMH, the IP_FHT, and the CL to form a new algorithm for detection of the tool flute breakage during end milling by using the feed-motor current signals. The effectiveness of the proposed monitoring approach has been demonstrated in case studies during end milling.

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Nonlinear Coupling Control Laws for an Underactuated Overhead Crane System

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***Abstract*—In this paper, we consider the regulation control problem for an underactuated overhead crane system. Motivated by recent passivity-based controllers for underactuated systems, we design several controllers that asymptotically regulate the planar gantry position and the payload angle. Specifically, utilizing LaSalle's invariant set theorem, we first illustrate how a simple proportional–derivative (PD) controller can be utilized to asymptotically regulate the overhead crane system. Motivated by the desire to achieve improved transient performance, we then present two nonlinear controllers that increase the coupling between the planar gantry position and the payload angle. Experimental results are provided to illustrate the improved performance of the nonlinear controllers over the simple PD controller.**

***Index Terms*—Energy damping, Lyapunov methods, nonlinear control, overhead crane.**

I. Introduction

Precise payload positioning by an overhead crane (especially when performed by an operator using only visual feedback to position the payload) is difficult due to the fact that the payload can exhibit a pendulum-like swinging motion. Motivated by the desire to achieve fast and precise payload positioning while mitigating performance and safety concerns associated with the swinging motion, several researchers have developed various controllers for overhead crane systems. For example, Yu *et al.* [29] utilized a time-scale separation approach to control an overhead crane system; however, an approximate linearized model of the crane was utilized to facilitate the construction of the error systems. In [27], Yashida *et al.* proposed a saturating control law based on a guaranteed cost control method for a linearized version of the crane system dynamics. Martindale *et al.* [18] utilized an approximate crane model to develop exact model knowledge and adaptive controllers while Butler *et al.* [2] exploited a modal decomposition technique to develop an adaptive controller. In [3], Chung and Hauser designed a nonlinear controller for regulating the swinging energy of the payload.

Several researchers have also examined the control problem for overhead crane systems with additional degree of freedom (DOF). Specifically, Moustafa and Ebeid [19] derived the nonlinear dynamic model for an overhead crane and then utilized a standard linear feedback controller based on a linearized state space model. In [20], Noakes and

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